Multi-objective power quality optimization of smart grid based on improved differential evolution

by

JOHN SAVECA

submitted in accordance with the requirements for
the degree of

MAGISTER TECHNOLOGIAE

in the subject

ELECTRICAL ENGINEERING

at the

UNIVERSITY OF SOUTH AFRICA

SUPERVISOR: Prof. Z WANG

OCTOBER 2018

DECLARATION

Name: JOHN SAVECA

Student number: 57116733

Degree: MAGISTER TECHNOLOGIAE ELECTRICAL ENGINEERING

Exact wording of the title of the dissertation as appearing on the copies submitted for examination:

MULTI-OBJECTIVE POWER QUALITY OPTIMIZATION

OF SMART GRID BASED ON IMPROVED

DIFFERENTIAL EVOLUTION

I declare that the above dissertation is my own work, I have not previously submitted this work, or part of it, for examination at UNISA for another qualification or at any other higher education institution and that all the sources that I have used or quoted have been indicated and acknowledged by means of complete references. I further declare that I submitted the thesis to originality checking software. The result summary is attached

27 September 2018

SIGNATURE DATE

This Dissertation is dedicated to Strong believers and hard workers who live to better the future generation.

Acknowledgement

First of all I would like to thank my supervisor Professor Zenghui Wang for giving me the opportunity to do my research under him and for his smart guidance, advises, dedication and effort he put in supervising me through my research. I thank him for making me be able to think and work smart and to be efficient with time during my research. I would also like to thank him for the motivations he gave me in order for me to work even harder to completing my master's research. I would also like to thank the Institution UNISA for giving me platform to study further in my field of study. I would like to thank UNISA for its electronic library access, it made the research completion possible. I would also like to thank for its motivation it put by giving me a bursary in order for me to be able to complete my research. Lastly I would like to thank my friends, family and a special person to me for always giving me motivation to push my studies harder.

Abstract

In the modern generation, Electric Power has become one of the fundamental needs for humans to survive. This is due to the dependence of continuous availability of power. However, for electric power to be available to the society, it has to pass through a number of complex stages. Through each stage power quality problems are experienced on the grid. Under-voltages and over-voltages are the most common electric problems experienced on the grid, causing industries and business firms losses of Billions of dollars each year. Researchers from different regions are attracted by an idea that will overcome all the electrical issues experienced in the traditional grid using Artificial Intelligence (AI). The idea is said to provide electric power that is sustainable, economical, reliable and efficient to the society based on Evolutionary Algorithms (EAs). The idea is Smart Grid. The research focused on Power Quality Optimization in Smart Grid based on improved Differential Evolution (DE), with the objective functions to minimize voltage swells, counterbalance voltage sags and eliminate voltage surges or spikes, while maximizing the power quality. During Differential Evolution improvement research, elimination of stagnation, better and fast convergence speed were achieved based on modification of DE's mutation schemes and parameter control selection. DE/Modi/2 and DE/Modi/3 modified mutation schemes proved to be the excellent improvement for DE algorithm by achieving excellent optimization results with regards to convergence speed and elimination of stagnation during simulations. The improved DE was used to optimize Power Quality in smart grid in combination with the reconfigured and modified Dynamic Voltage Restorer (DVR). Excellent convergence results of voltage swells and voltage sags minimization were achieved based on application of multi-objective parallel operation strategy during simulations. MATLAB was used to model the proposed solution and experimental simulations.

KEY TERMS: Smart Grid, Power Quality, Evolutionary Algorithm, Differential Evolution, Multi-Objective, Optimization, Mutation Schemes, Convergence speed, Dynamic Voltage Restorer, Sags, Swells, Power Network, Parallel Operation.

Table of contents **Page**

Declaration		i
Dedication		ii
Acknowledgement		iii
Abstract		iv
Table of Contents		v
List of Figures		viii
List of Tables		xi
Acronyms and Abbreviations		xii
Chapter 1:	Introduction	1
1.1	Background of the study	1
1.2	Problem statement	3
1.3	Research Objectives	4
1.3.1	Main Objectives	4
1.3.2	Specific Objectives of the Study	4
1.4	Limitations of the study	5
1.5	Hypothesis	5
1.6	Expected contribution of the study	5
1.7	Methodology Overview	6
1.8	Outline of Final Dissertation	7
Chapter 2:	Literature review	9
2.1	Previous researches done on power quality and differential Evolution	9

2.1.1. Study previously done on smart grid 9

2.1.2. Study previously done on Power Quality 13

2.1.3. Study previously done on other Evolutionary Algorithms 16

2.1.4. Study previously done on Differential Evolution 16

2.1.5. Study previously done on Dynamic Voltage Restorer 18

2.2 Theory contributing towards the research 20

2.2.1 Smart grid overview 20

2.2.2 Smart Grid vision on communications 21

2.2.3 Smart Grid Automation and Controls technology vision 24

2.2.4 Smart Grid Renewable Energy Sources vision 26

2.3 Power problems in Smart grid 28

2.4 Dynamic Voltage Restorer 34

2.4.1. DVR Compensation Techniques 37

2.5 Multi-Objective Optimization 38

2.6 Differential Evolution Algorithm 41

2.6.1 Population Structure 42

2.6.2 Initialization 42

2.6.3 Mutation 43

2.6.4 Crossover 43

2.6.5 Selection 44

2.7 Conclusion 44

Chapter 3: Improved Differential Evolution Based on Mutation Strategies 45

3.1	Differential Evolution Overview	45
	3.1.1 Classical Differential Evolution	46
3.2	DE Improvement	47
3.3	Methodology	48
3.4	Results	50
3.5	Conclusion	59
Chapter 4:	Dynamic Voltage Restorer Based Power Quality Optimization Using Improved Differential Evolution Algorithm	60
4.1	Smart Grid Overview	60
4.2	Power Quality Overview	60
4.3	Proposed multi-objective power quality optimization based On improved differential evolution	61
4.4	Methodology	66
4.5	Results and Discussion	68
4.6	Conclusion	76
Chapter 5:	Conclusion and Future works	77
	5.1 Conclusion	77
	5.2 Future Works	78
Publications:		79
References		80
Appendices		87
	Appendix A: DE matlab code for improved DE based on Mutation Strategies:	87
	Appendix B: DVR Power Quality Optimization	93

Appendix C: Research Ethical Clearance Letter 99

List of Figures Page

Figure 2.1: comparison of DE optimized and unoptimized values. 17

Figure 2.2: Communication network illustration with regards to space in Smart Grid 21

Figure 2.3: Smart Grid communication Infrastructure 24

Figure 2.4: Photovoltaic Solar panels 27

Figure 2.5: Block diagram for Photovoltaic solar system 27

Figure 2.6: Positive impulsive transient 28

Figure 2.7: Oscillatory transient caused by automatically switching in capacitor banks 29

Figure 2.8: Sustained power interruption 30

Figure 2.9a: voltage sags 31

Figure 2.9b: under-voltage 31

Figure 2.10a: Voltage swells 31

Figure 2.10b: Over-voltage 31

Figure 2.11 DC offset 32

Figure 2.12: Harmonics distortion waveform 32

Figure 2.13: Inter-harmonics waveform distortion 32

Figure 2.14: Notching waveform 33

Figure 2.15: Noise waveform 33

Figure 2.16: Voltage fluctuations 33

Figure 2.17: Frequency variations 34

Figure 2.18: DVR location in Power system 35

Figure 2.19: DVR schematic Diagram 36

Figure 2.20: Equivalent DVR circuit diagram 36

Figure 2.21: Steps involves differential evolution algorithm 41

Figure 3.1: pseudo- code of DE/Modi/3. 49

Figure 3.2: Rastrigin’s fitness vs iterations 56

Figure 3.3: Schwefel’s finess vs iterations 57

Figure 3.4: Ackley’s fitness vs iterations 57

Figure 3.5: Rastrigin’s fitness vs iterations 57

Figure 3.6: Sum-Power’s fitness vs iterations 58

Figure 3.7: Sum-Square’s fitness vs iterations 58

Figure 3.8: Griewank’s fitness vs iterations 58

Figure 3.9: Bukin’s fitness vs iterations 59

Figure 4.1: DVR system for Sag and swell Compensation 62

Figure 4.2: Control Circuit for DVR 62

Figure 4.3: Voltage swell fault generator 63

Figure 4.4: Voltage sag fault generator 63

Figure 4.5: Voltage Compensator system 63

Figure 4.6: DE/Modi/3 pseudo- code for multi-objective 67

Figure 4.7: Load voltage behaviour with DVR disconnected from the system 69

Figure 4.8: Load voltage behaviour with DVR connected to the system 69

Figure 4.9: Load voltage during voltage sag disturbance 70

Figure 4.10: Compensation voltage from DVR 71

Figure 4.11: Load voltage after compensation 71

Figure 4.12: Load voltage during voltage swell disturbance 72

Figure 4.13: Correction voltage from DVR 72

Figure 4.14: Load voltage after correction 73

Figure 4.15: Sag and swell effects after voltage correction from DVR 73

Figure 4.16: Multi-objective minimization based on DE/Rand/1 75

Figure 4.17: Multi-objective minimization based on DE/Modi/2 75

Figure 4.18: Multi-objective minimization based on DE/Modi/3 76

List of Tables Page

Table 1.1: Financial loss due to Power Quality incidents 2

Table 2.1: SR values of the objective function for each algorithm 16

Table 2.2: DE optimized and unoptimized values 17

Table 2.3: comparison between DE and IDE results 18

Table 2.4: Different indices in both algorithms 19

Table 3.1A: DE/rand/1 Results 51

Table 3.1B: DE/rand/1 Results 51

Table 3.2A: DE/Modi/1 Results 52

Table 3.2B: DE/Modi/1 Results 52

Table 3.3A: DE/Modi/2 Results 53

Table 3.3B: DE/Modi/2 Results 53

Table 3.4A: DE/Modi/3 Results 54

Table 3.4B: DE/Modi/3 Results 54

Table 4.5: Statistical Data for Mutation strategies 55

Table 3.6: Time complexity 56

Table 4.1: DE/Rand/1 fitness for Sags and Swells 74

Table 4.2: Statistical Data Analysis 74

Acronyms and Abbreviations

2G	Second Generation of Cellular
2.5G	Second and Half Generation of Cellular
3G	Third Generation of Cellular
AC	Alternate Current
ACO	Ant Colony Optimization
AMI	Advanced Metering Infrastructure
B2B	Back-to-Back
CAPSO	Chaotic Accelerated Particle Swarm Optimization
DC	Direct Current
DE	Differential Evolution
DE/Modi/1	Differential Evolution Modification number1
DE/Modi/2	Differential Evolution Modification number 2
DE/Modi/3	Differential Evolution Modification number 3
DE/Rand/1	Differential Evolution Rand number 1
DG	Distributed Generation
DSL	Digital Subscriber Lines
DSTATCOM	Distribution Static synchronous Compensator
DVR	Dynamic Voltage Restorer
EA	Evolutionary Algorithms
EO	Evolutionary Optimization
EV	Electric Vehicles
FAN	Field Area Network
FACT	Flexible Alternating Current Transmission Systems
GA	Genetic Algorithm
HAN	Home Area Network
Hz	Herts

IEEE	Institute of Electrical and Electronics Engineers
LV/MV	Low-Voltage/Medium Voltage
LTE	Long Term Evolution
MA	Memetic Algorithm
MAN	Metropolitan Area Network
MATLAB	Matrix Laboratory
MB	Megabyte
MOV	Metal Oxide Varistor
NAN	Neighbourhood Area Network
NIST	National Institute for Standards and Technology
NL	Normal Load
ns	nanoseconds
OLTC	ON Load Tap Changer
PC	Personal Computer
PCC	Point of Common Coupling
PI	Internet Protocol
PLC	Powerline Communication
PMU	Phasor Measurement Unit
PV	Photovoltaic
S	Seconds
SC	Shunt Capacitor
SEP	Smart Energy Profile
SLBC	Smart Load with Back-to-Back Converter
SLQ	Smart Load with only Reactive Compensation
THD	Total Harmonic Distortion
TVSS	Transient Voltage Surge Suppressors
UPS	Uninterruptible Power Supply
Var	Volt amperes reactive

VR	Voltage Regulator
VSI	Voltage Source Inverter
VVC	Volt/VAr Control
WAN	Wide Area Network
WiMAX	Worldwide Interoperability for Microwave Access

CHAPTER 1

INTRODUCTION

1.1. Background of the Study

The modern society has become much more dependent on the continuous availability of electric power, and that has made electric power to become one of the human's fundamental needs of the modern age. However, for one to get access to it, a number of complex stages are involved, from the generation of power to the transmission, using long distance and short distance transmission lines up to where it is distributed to the households and industries. Through each stage there are technical issues experienced by the power grid. Under-voltage (voltage sags), over-voltage (voltage swells), voltage surges and voltage spikes are amongst the problems experienced in the power grid, they cause mal-operation of the electric equipment, increase in power loss and over burdening of the power system **(Dhomane, et al., 2016)**. A modernized power grid (smart grid) is set to overcome all electrical issues involved in every stage where the electric power is passed, and that will create a power that is sustainable, economical, reliable and efficient to the society as a whole. The term Smart grid has been defined by many organizations, one organization defined smart grid as an automated electric power grid, that performs based on the analogue or digital information it collects using Information and Communication Technology (ICT), such as information about the actions of the suppliers and consumers, in order to improve the generation, transmission and distribution of electricity that is efficient, reliable, economical and sustainable to the society**(Subhalakshmipriya & Suganya, 2015).**

Various researchers from different perspectives are attracted by smart grid's vision of transforming the traditional power grid into an integrated state of the art future generation power grid**(KarthiKeyan, et al., 2016)**. The aim of the smart grid concept is to provide electric power quality that is environmental free from greenhouse gas, electrical system that is economically evolved and technologically integrated, intelligently integrated communication and control system to the power grid, to sustain energy for the future generation. However there are still many various goals the smart grid concept wishes to archive. The top priority of worldwide energy utility companies at the moment is to increase energy efficiency while maintaining a clean environment from greenhouse gases by adopting renewable energy sources and an accelerated development of smart grid technology**(Ceaki, et al., 2017)**.

Electricity users such as businesses, homes, industrial companies including the electric utilities, are much more concerned about the study of power quality and ways to control it. This comes as a result of equipment becoming more sensitive to even small changes in the supply voltage, current, and frequency. The power disturbance definition defined by most institution states that, power disturbance is any interruption of voltage, current or frequency that opposes normal functioning of the power system**(Seymour & Horsley, 2008).** Reliability of smart grid also depends on power quality, therefore making power quality one of the important and responsible aspects in smart grid's vision**(Agarwal & Tsoukalas, 2011).**

According to a study conducted by **Electric Power Research Institute, 2001,** it shows that an approximately amount of $45.7 billion is being lost by industries and business firms each year, due to power disturbances in USA. Power disturbances are responsible for a loss of an estimated amount of $104 billion to $164 billion across all business sectors, and all other quality problems are responsible for an estimated amount of $15 billion to $24 billion(**Seymour & Horsley, 2008**).

Another study of COST OF POOR POWER QUALITY conducted by **European Copper Institute** described Poor Power Quality as any occurrence related to the power networks that is responsible for any financial loss. There are many effects cause by poor power quality in large industries, some are malfunction and overheating of electrical equipment, power supply failure that results in blowing of fuses and tripping of circuit breakers, damage to sensitive equipment such as computers and production line control systems and interferences of electronic communications to name few. Such occurrences result in system outage, inefficient running and a reduced life span of electrical installations. Eventually that result in high running costs of installations, leading to the production being stopped and major costs being incurred. Table1 below gives an overview of financial losses due to poor power quality installation incidents in different industries, conducted by **European Copper Institute** (**Schipman & François Delincé, 2010).**

Table 1.1: Financial loss due to Power Quality incidents(Schipman & François Delincé, 2010).

Sector	Financial loss per incident
Semi-conductors production(*)	3800000 €
Financial trade(*)	6000000 € per hour
Computer center(*)	750000 €
Telecommunication(*)	30000 € per minute
Steel industry(*)	350000 €
Glass industry(*)	250000 €
Offshore platforms	250000-750000 € per day
Dredging/land reclamation	50000 – 250000 € per day

For the requirements of smart grid concept to be archived, a set of artificial intelligent based methods are adopted to assess and solve smart grid's problems**(Ceaki, et al., 2017)**. . Evolutionary Algorithms (EA) are genetic population-based metaheuristic optimization algorithms that form random search and optimization procedures by following natural evolutionary principles. Evolutionary optimization (EO) techniques find and maintain multiple solutions in one single simulation run, while direct search and optimization procedures use a single solution update during iterations and they use a deterministic transition rule. That's what distinguishes Evolutionary algorithms from direct search and optimization procedures**(Okinda & Odero, 2016).** There are different types of EAs used in optimization problems, one of them being Differential Evolution (DE) Algorithm. Differential Evolution Algorithm has remarkably been regarded as one of the most effective global optimizer for optimization problems in the research field of science and engineering since its inception in 1995. DE is a Global Optimization method that is easy to use, simple to implement, fast and reliable to converge to true optimum, therefore these are the facts that make DE to be regarded as one of the best global optimizer(**Price, et al., 2005)**. Since DE was introduced by Storn and Price, many new improved DE algorithms have been proposed, with most of them focusing on choosing proper control of the parameters**(Fang & Jie, 2016).** The research will focus on power quality optimization in smart grid, based on an improved Differential Evolution Algorithm, with the objective functions of counterbalancing voltage sags, minimizing voltage swells and eliminating voltage surges or spikes in order to achieve a better voltage profile.

1.2. Problem statement and Research Question

Power distribution system is experiencing lack of improvement compared to the generation and transmission in the smart grid concept. Various technologies have been introduced to generation and transmission systems, making them evolve and improve under the control of utility companies. For the distribution system, it has been difficult for it to evolve and improve, this is due to the number of stakeholders involved in the process**(KarthiKeyan, et al., 2016)**. For that reason, distribution system has challenges in delivering best quality power required by households and industries. Sudden over-voltages (voltage swells, Voltage spikes and voltage surges) and under-voltages (voltage sags) are encountered by households and industries, causing damage, inefficient and erratic operation of the electric equipment. Electrical disturbances such as power interruptions, transients, harmonics, swells and sags are the major contributors towards the poor power quality**(Hojabri & Toudeshki, 2013)**. Deficient power quality has a negative Impact towards the reliability and sustainability of electricity to the society and future generation, and it also has negative impact to the economy, and that can fail smart grid's mission to provide power that is efficient, reliable, economical and sustainable to the modern and future generation. Despite DE algorithm being regarded as one of the best reliable and efficient EA method for solving optimization problems, it also has its own limitations. As reported by **(Prakash, et al., 2016),** DE experiences Stagnation and premature convergence. DE is also extremely affected when the algorithm specific parameters are badly adjusted.

Different control Parameter selections and mutation schemes will be searched and developed in order to improve Differential Evolution Algorithm convergence, then a Multi-objective Power quality optimization will be developed in smart grid based on the improved differential evolution algorithm, with the objective functions of counterbalancing voltage sags, minimizing voltage swells to the required set point and eliminating voltage surges or spikes, in order to achieve a better voltage profile in the distribution system, improving efficient operation for electrical equipment and accomplishing a requirement for a successful smart grid concept. The following question will be answered: *How can Power quality be improved in the distribution system to satisfy the standard requirement for a successful smart grid concept?*

General Challenges

- Power distribution system lacks improvement, leading to one of the smart grid's requirement to deliver quality power unfulfilled.
- It is difficult for the distribution system to improve due to number of stakeholders involved.
- The Distribution system is facing challenges in terms of delivering the best power quality to end-users.

Sub-Problems

- Unexpected voltage sags and voltage swell are experienced in households and industries, resulting in damage, malfunction and inefficient operation to electrical and electronics equipment.
- Reliable and effective electric supply to the society and manufacturing industries is strongly affected by voltage sags and swells, leading to smart grid's mission to provide power that is reliable, effective and safe to the society and industries being unsuccessful.
- Differential Evolution experiences stagnated, slow and ineffective convergence when solving a global optimization problem and it is severely affected when parameters are inadequately modified.

1.3. Research Objectives

1.3.1. Main Objective

The main objective of the study is to improve power quality in Smart Grid distribution system by developing an improved DE and applying the improved DE to minimize voltage swells and sags, while maximizing the power quality in Smart Grid distribution systems.

1.3.2. Specific Objectives

The specific objectives of this research are,

- To reduce stagnation and premature convergence of the Differential Evolution Algorithm.
- To investigate a better control for badly adjusted algorithm specific parameters for Differential Evolution.
- To reduce voltage swells, counterbalance voltage sags, and eliminate voltage spikes and surges encountered by households and industries.
- To reduce damage, inefficient and erratic operation of the electric equipment caused by power disturbances to the households and industries.

1.4. Limitations

This research will be limited to…

- Distribution system and smart grid.
- Power Quality Control and Optimization.
- Voltage sags, Voltage swells, Voltage spikes and voltage surges.
- Computer modeling and simulations for the validation of research results since there is no facility to perform the practical experiments.
- For solving the research problem, Differential Evolution will be used and the schematics that will to be focused on are Dynamic Voltage Restorer (DVR), Transient Voltage Surge Suppressors (TVSS) and Thyristor Based Static Switch.

1.5. Hypothesis

Power quality can be improved if voltage sags, swells, spikes and surges are controlled to the best required voltage set point. The instability of the voltage to the end-users influences the power to the load not to be stable as well. This is due to direct proportionality between the power and the voltage. Power instability causes damage, malfunction and inefficient operation to the load. If the voltage to the end-users is stabilized, the power to the load will be stable and the load will not experience malfunctions and will operate efficiently. Reliability and effectiveness for electric supply to the society and manufacturing industries can also be improved by minimizing both voltage sags and swells. Modification of mutation strategies in DE can help improve speed, effectiveness and reliable convergence to optimization problem.

1.6. Benefits of the study

- The study will significantly improve efficient operation of electrical equipment in households and industries, preventing product stoppage and interruptions which in return will prevent financial losses in large companies and making a significant improvement to the economy of the country.

- The society and will be enriched with an improved efficient, sustainable and intelligently controlled quality electric power, as well as a better knowledge to maintain that electrical power for future generation.
- The study will also make a significant contribution towards smart grid's vision and mission to better the current power system by delivering economical, sustainable, flexible and efficient quality power to the households and industries.
- The study will expand knowledge in smart grid and Differential Evolution Algorithm for future research developments.

1.7. Methodology Overview

For this research, Quantitative research method is used, due to its nature of stressing objective measurements and mathematical analysis of data gathered through various experiments and simulations or through influencing of pre-existing data of statistics employing computational strategies. Therefore this research also involves collection, analysis and communication of measurable data. Numerical based comparisons of data are done and the results are based and judged on data comparisons. The research also involves theory testing and researcher's opinion based on data analysis through publication of obtained results on the conference proceedings. The research problem is of technical nature and therefore falls in science and engineering field, therefore quantitative research method is a suitable method for this research.

Under Quantitative research method, Deductive approach is used because of its concern in developing hypothesis on the basis of existing theory and designing of research strategies to test the hypothesis, therefore this research involves hypothesis based on physical laws and known facts. Experimental simulations are made and based on observation of obtained results, the hypothesis is accept or rejected.

For Differential Evolution improvement, the aim is to enhance DE speed on the basis of convergence. In consequence of that, the focus is based on modification of mutation schemes and selection of control parameters. DE/Rand/1 mutation scheme is selected as a reference for this research due to its simplicity to implement and robust convergence. The modified mutation schemes from DE/Rand/1 reference are tested using the most commonly used benchmark functions. During simulation tests, the selection of control parameter is conducted by tuning population Size (PS), Crossover rate (Cr) and Amplification factor (F), in reference to classical mutation schemes and modified mutation schemes in order to identify the best combination of control parameters and mutation schemes. There results of every simulation are tabled.

Statistical data analysis table, time complexity table and Simulation figures are used to analyze the data collected. The conclusion is made with the aid of analysis of the data collected during experimental simulations. The combination of best mutation scheme and the best tuned parameters must give the best convergence and eliminate stagnation in DE algorithm. The benchmark functions that are used are Sphere Function, Ackley function, Rastrogin function, Griewank Function, SumPower Function, Schwefel Function, Bukin Function and SumSquare Function.

For optimization of power quality in smart grid, the improved DE is used. The focus of this section is to minimize distribution network voltage problems while maximizing the power quality of the network. Following are the objective functions focused on during the research:

1. Counterbalancing voltage sags
2. Minimization of voltage swells
3. Elimination of voltage surges or spikes
4. Maximizing power quality power at near end users.

A circuit schematic to achieve the above mentioned objective functions is developed based on combination, reconfiguration and modification of the following previously used schematics and devices: Dynamic Voltage Restorer (DVR), Transient Voltage Surge Suppressors (TVSS) and Thyristor Based Static Switch. The following components are used for modification of a developed schematics circuit: Inductors, Capacitors, diodes and resistors. MATLAB Simulink is used to develop and test the circuit schematic.

After the tests are done on the developed circuit schematic on Simulink, improved DE is applied to optimize the developed schematic based on its improved version, with the same objective functions as mentioned above. The optimized circuit schematic must be able to minimize voltage swells on the distribution network, counterbalance voltage sags experienced on the network and completely eliminate voltage surges and spikes from the network, thereby maximizing power quality to the end users in order to achieve one of the smart grid's Vision of providing best power quality to the modern and future generation.

Several simulations under different conditions are made in order to verify that the proposed solution is not a fluke and it is able to serve the purpose it's proposed to serve under different conditions. Data is collected during each simulation under each condition. Statistical data analysis table and simulation figures are used to analyze the collected data after simulations. Conclusion and opinion is made based on the analysis of data.

1.8. Outline of Final Dissertation

The final dissertation of the research consists of five chapters. The chapters provides a detailed process from the identification of the research problem and the review of the literature to the setting up of methods of solving the problems, as well as results that are obtained during the simulation of the solution.

Chapter 1 gives the review of the identification of the research problem, the objectives and benefits of the study and the hypothesis of the research conducted.

Chapter 2 gives the literature review of the study of power quality optimization in smart grid and Differential Evolution Algorithm. The chapter gives the history and overview of the power grid. It gives the overview of the selected Distribution network Problems and overview of the selected previously used mitigating technics of the power quality problems. The chapter also gives the theories and information that contributes the improvement of Differential Evolution and power quality optimization.

Chapter 3 focuses on Differential Evolution Algorithm improvement with regards to convergence speed and elimination of stagnation. The improvement of Differential Evolution focuses on modification of mutation strategies and MATLAB tool is used to model the proposed solution.

Chapter 4 focuses on optimization of smart grid power quality by applying the improved differential evolution in combination with a reconfigured and modified Dynamic Voltage Restorer (DVR) as well as involving multi-objective optimization using parallel operation strategy.

Chapter 5 gives the conclusion of the research and the future works. After chapter six, the appendix and references follow. The referencing is done using Mendeley referencing tool.

CHAPTER 2

LATERATURE REVIEW

This chapter gives the review of previously done studies on Smart Grid, Power Quality, Evolutionary Algorithms, Differential Evolution and Dynamic Voltage restorer. The chapter further gives theories contributing to the proposed study by reviewing Smart grid and its challenges, Multi-Objective Optimization, Differential Evolution, Power Quality and Dynamic Voltage restorer. On the above mentioned reviews, the chapter attempts to detail every study and theory in other to archive adequate understanding on the study.

2.1. Previous researches done on power quality and differential evolution

2.1.1. Study previously done on smart grid

The concept **Smart grid** has been defined differently by many researchers and there have been different aspects with the concept of smart grid. One institution defined Smart Grid as a computerized modern age electrical power grid that is entirely networked, controlled, instrumented and automated to collect and act on the ICT information in fulfillment to deliver the needed power to the end users. Smart Grid is a pure networked intelligent power grid that uses Internet Protocol (IP) addresses to link and access major components, such as generators, relays, transformers and electrical meters in the power system. Sensors and processors are equipped to most components to enable them to intelligently execute information without involving human effort. Power resources that are available in the Smart Grid are conventional types of generating plants and small-scale renewable Distributed Energy Resources **(Nygard, & Ranganathan, 2011).** The focus of Smart Grid is to provide quality power that meet 21st century demand which co-operative generation and storage options that fulfills customer's needs considering the changes and the challenges. The key goal of smart grid is to encourage active customer involvement and decision making as well as to build the functional environment in which both power utilities and electricity users influence each other **(Phuangpornpitaka & Tiab, 2013)**. Many researchers have used the Artificial Evolutionary process known as **Evolutionary Algorithms** to find the results in smart grid research problems. However that's because Evolutionary algorithms are capable of performing solutions that are approximate to almost all types of problems since they do not make assumptions about the underlying fitness landscape, and that can be concluded because of its success in solving problems in diverse fields as engineering where it solves the optimization problems **(Jung, et al., 2017).** Power Quality problems in Smart Grid has been one of the focus subject by many researchers in developing an intelligent power Grid, below is how different researchers approached power quality problems and smart grid.

Smart grid technology is associated with various interesting ideas from various researchers, with a common goal of bettering the new age power system. Some of the research Institutes have focused on smart grid capability of self-healing. However, for smart grid to be able to do the self-healing, a fault detection technology has to be considered, necessary fault isolation equipment must be equipped in the grid and automated recovery of the system has be configured**(Bush, 2014).** For all the above mentioned sections of self-healing to operate, a smart grid Information and communication Technology (ICT) is required to send and receive information regarding any fault problem experienced at a specific part of the grid, the ICT is needed to send information to the isolation equipment to isolate the faulty part of the system, and finally the automated recovery system requires information to recover operation of the grid. This makes ICT one of the focuses on developing intelligent power grid. ICT has a wide range of responsibility on smart grid. It includes but not limited to monitoring, protection and control of the grid. However, the growing interest on communication networks for smart grid support brings about certain drawbacks, such as cyber-attack and complex that leads to instable and inefficient communication on the grid. For that, more study branches of smart grid are raised for future research generation**(Han, et al., 2016).**

With forever increasing researches about the integration of renewable energy sources in the smart grid, it is believed that many power and voltage quality issues are experienced in the grid due to their unstable power generation from the solar and wind. A solar System Connected Grid of a Controlled Single-Phase Voltage with a Functionality of Power Quality Conditioner was proposed. The focus was to introduce a photovoltaic system of a single-phase type that provides support to grid voltage and harmonic distortion compensation at the point of common coupling (PCC). The problem was approached by using a controlled voltage converter that acts as a shunt controller for voltage quality improvement in case of small voltage dips and nonlinear loads presence. To stabilize and improve voltage profile, shunt controllers were used as generators of static Var in power systems and they were also used for current harmonics and unbalanced load current compensation. It was also studied that by independently adjusting the active and reactive power, voltage frequency and amplitude of the grid are determined. The conclusions were based on control of frequency and voltage drop through active and reactive power respectively **(Guerrero, 2006).** The study was presented by the following formulas, where angle of power δ is small, therefore $\sin\delta \cong \delta$ and $\cos\delta \cong 1$.

$$\delta \cong \frac{XP_A}{V_A V_B} \tag{2.1}$$

$$V_A - V_B \cong \frac{XQ_A}{V_A} \tag{2.2}$$

The study based on the Shunt Controller was made and it was found that, Shunt devices are normally adopted for compensation of small voltage variations which are controllable by injection of reactive power. The shunt controller can be controlled by current or voltage. When the converter is controlled by current it can be represented as a component of grid that adjusts grid reactive output power according to the grid voltage variations to support the grid voltage. During the occurrence of voltage sag, the load voltage is supported by reactive power provided by the converter and the grid current Ig has a reactive component that is dominant. The following formulas present the study.

$$\bar{I}_g + \bar{I}_c = \bar{I}_{load} \tag{2.3}$$

$$\bar{I}_g = \frac{\overline{V_{LG}}}{j\omega L} \tag{2.4}$$

The grid current amplitude depends on the grid impedance value where V_{Lg} is the voltage drop of the inductance. Under normal conditions, the shunt controller supplies a compensating current $I_c = I_{load}$ if it supplies all the active and reactive power requested by load, these causes the system to operate as in island mode and $I_g = 0$. The simulation and experiment of the proposed study was conducted. It was noticed that for Voltage sag compensation, the load voltage remains constant and equal to the desired voltage level during voltage dip. In order to compensate the load voltage, reactive current injected into the grid by shunt-connected converter, and the current is mainly capacitive. For Voltage harmonic compensation, the load voltage appears highly distorted before connecting the shunt converter, and the voltage THD is around 17%. The introduction of voltage harmonics is caused by the distorting load in the system where the voltage THD is 2%.The shunt-converter compensates voltage harmonics when connected to the grid. The results confirm the proposed solution validity in case of voltage dips and nonlinear loads **(Mastromauro & Liserre, 2009)**. However there were still other voltage quality problems not covered such as voltage swells and total power interruption on the smart grid.

Another researcher pointed out that the increase of Distributed generation such as solar system generation causes over-voltage problems in low and medium voltage distribution networks, while under voltage problems could be led by the charging of electric vehicles during the night**(Akhtar, et al., 2017).** Another research was conducted based on the voltage quality problems that are found in the smart grid due to Photovoltaic (PV) power generation and charging of electric vehicle on low voltage distribution systems. Voltage Control by Smart Loads (SL) in Distribution Networks was proposed. A smart load configuration with one converter was previously reported and developed, however it had limitations. The limitations were due the dependence of its active and reactive power consumption on each other, therefore a simultaneous control was impossible for both active and reactive power of the Smart Load, only one of them could be controlled (either active or reactive power) to control the supply voltage, depending on the resistance over reactance(R/X) ratio of the system**(Akhtar, et al., 2017)**. The limitations were overcame by a proposed improvement of a back to back configured additional shunt converter to assist exchanged active power by the series converter, which increased smart load's flexibility without any energy storage required**(Akhtar, et al., 2017)**. AC-to-DC Bidirectional converters were used, with the ac side connected to the power grid. The inserted voltage magnitude V_{ES} and phase angle θ_{ES} were set to be controlled by converter 1. Voltage V_{dc} across the dc link was maintained by connecting converter 2 parallel to the supply, supporting exchanged active power by series converter 1. The voltage at the supply (V_C) was expressed as the phasor sum of the voltage (V_{NC}) of NC load and the compensator voltage (V_{ES}).

$$V_C\angle\theta_C = V_{NC}\angle\emptyset_{NC} + V_{ES}\angle\theta_{ES} \tag{2.5}$$

where θ_C denotes the supply voltage phase angle, θ_{ES} denotes the compensator voltage phase and ϕ_{NC} denotes the angle of NC load impedance. The above equation was further expressed as,

$$V^2_c = V^2_{NC} + V^2_{ES} + 2V_{NC}V_{ES}\cos(\emptyset_{NC} - \theta_{ES}) \tag{2.6}$$

$$V_{NC} = -V_{ES}\cos(\emptyset_{NC} - \theta_{ES}) \pm\sqrt{V_C^2 - V_{ES}^2\sin(\emptyset_{NC} - \theta_{ES})^2} \tag{2.7}$$

$$F(V_C, V_{ES}, \theta_{ES}) \tag{2.8}$$

$$P_{SL} = P_{NC} = \frac{V_{NC}^2\cos(\emptyset_{NC})}{Z_{NC}} \tag{2.9}$$

$$Q_{SL} = Q_{ES} + Q_{NC} \tag{2.10}$$

$$Q_{SL} = \frac{\pm V_{ES}V_{NC}}{Z_{NC}} + \frac{V_{NC}^2\sin(\emptyset_{NC})}{Z_{NC}} \tag{2.11}$$

The effectiveness of voltage control by SLQs and SLBCs was compared by running simulations on MATLAB Simulink under various conditions, which are under-voltage and over-voltage conditions. The load was connected at the far end of the feeder during the simulation, and the results were taken. The results showed that, on normal load (NL), the voltage supply goes up to a maximum of 1.086 p.u. during midday, while during the late evening peak it goes as low as 0.925 p.u. According to the report, SLBC could restore back the voltage within the allowable range of ±0.05 p.u. On the other hand, SLQ could only restore the voltage in under-voltage situation, and it could not restore voltage in case of over-voltage situation. SLQ and the SLBC acts like a Normal Load under voltage supply within the permissible range of ±0.05 p.u., which results in overlapping traces. A larger change was noticed on NC load voltage (VNC) for SLBC as compared to the NC load voltage (VNC) for the SLQ. Observed Power variations explained the voltage responses. The observation showed that SLBC's active and reactive power increases above or decreases below the normal value to restore the system voltage during the over-voltage or under-voltage condition. However, in SLQ situation, an increase in active power is followed by a large decrease in the reactive power, which makes SLQ less effective in regulating the supply voltage as compared to SLBC**(Akhtar, et al., 2017)**.

2.1.2. Study previously done on Power Quality

A study was proposed for Voltage Control in Distribution Networks based on theoretic game Perspective. The focus of the study was to seek contribution in the compensation domain of reactive power by stabilizing local controllers of Volt/VAr. However the study used the approach of a dynamical system that is nonlinear with non-incremental local Volt/VAr control, casting of the Volt/VAr dynamics as a game, and the leveraging of the Theorem of fixed-point as well as mapping argument relating directly to contraction **(Zhou, et al., 2016).** The employments of nonlinear alternative current power flow models that are exact, were to be used in order to characterize the nature of Volt/VAr. The use of a reverse-engineering method was to be used to place the non-incremental Volt/VAr control with nonlinear dynamical system as a game, where each node behaves as a "selfish player" who employs its local control function as a best-response technique for its own cost function minimization. The method was used to prove the equivalence of equilibrium of the Volt/VAr control dynamics and equilibrium of the resulting game, and also to prove the uniqueness and existence of the equilibrium by providing leverage to the theorem of fixed-point as well as mapping argument contraction **(Zhou, et al., 2016).** During the approach of the study the following formulas were derived. v^0; p^c; p^g; q^c were given constants, and reactive powers $q^g = (q^g_1 \ldots\ldots q^g_n)$ were control variables. The power flow model formula was found to be:

$$P_{ij} = p^c{}_j - p^g{}_j + \sum_{k:(j,k)\in\mathcal{L}} P_{jk} + r_{ij}\ell_{ij} \tag{2.12}$$

$$Q_{ij} = q^c{}_j - q^g{}_j + \sum_{k:(j,k)\in\mathcal{L}} Q_{jk} + x_{ij}\ell_{ij} \tag{2.13}$$

$$v_j = v_i - 2(r_{ij} P_{ij} + x_{ij} Q_{ij}) + (r_{ij}^2 + x_{ij}^2)\,\ell_{ij} \tag{2.14}$$

$$\ell_{ij}\, v_i = P_{ij}^2 + Q_{ij}^2 \tag{2.15}$$

The power flow equation was represented as:

$$F\,(P, Q, \ell, v, q) = 0 \tag{2.16}$$

For the local volt/VAr control on the network power distribution, the aim was to modify the reactive power outputs $q^g = (q^g_1 \ldots\ldots q^g_n)$ so that the node voltages $v = (v_1 \ldots\ldots v_n)$ are maintained within a given range around their nominal values. The Volt/VAr was modeled to be as a control mechanism feedback with state $((t); (t))$, where the state of the current $((t); q(t))$ is mapped to the new injections of reactive power $q(t + 1)$. Most of the time $q(t + 1)$ is either completely or partly determined by a certain control function of Volt/VAr. For a voltage control game, the reactive power $q(t+1)$ is the solitary solution of the following optimization problem:

$$q(t+1) = \arg\min_{q_i \in \boldsymbol{\Omega\Omega}} u_i(q_i; v_i(t)), \tag{2.17}$$

where,

$$(;) := C_i(q_i) + q_i v_i \tag{2.18}$$

The results motivate to cast the dynamics as a game. Each node is viewed as a player with technique space and a cost function (;()). During the simulation setup the alternative current power flow model was computed by MATLAB tool MATPOWER. The piece wise linear droop control functions ware used with their slopes to be determined and analyzed. It was assumed that all the control functions have identical acceptable voltage range:

$[0.98^{p.u.}, 1.02^{p.u.}]$, i.e., $\delta_i = 0.04^{p.u.}, \forall i \in \mathcal{N}$.

The effects of reactive power injections upon voltage values was examined by fixing the reactive power injections of all inverters as 0 except one of them at the bus. One of the inverters on the bus bar that was not fixed was swept with the reactive power injections from-1MW to 1MW with granularity of 0.1MW and the recording of the effect of voltage changes at all buses was made. The results of the same nature were noticed by engaging any other inverters. It was concluded that in order to analytically characterize the local Volt/VAr control dynamics equilibrium and convergence with nonlinear power flow model, the dynamical system is reverse-engineered with non-incremental control as a voltage control game. The uniqueness, convergence and existence of the equilibrium are found by the theorem of fixed-point and mapping argument pertinent contraction. The results are also extended to the incremental Volt/VAr controls.

Another research on Voltage quality problems was done, based on Bio-inspired Evolutionary Algorithms Applied to Volt/VAr Control Optimization Problem in Smart Grid Context. The research employed the use of Evolutionary Algorithms methods to solve Voltage quality optimization Problem, using an improved Volt/VAr Control, based on configuration of distribution system approach. As reported, the approach allowed a full harmonious combination between the equipment used for control of reactive power and voltage. The approach also allowed system's global optimization with functional objectives that are flexible. VVC is also able to adjust to any network remodeling and level of penetration by distributed generation in the system. However three EA methods were selected to solve the voltage quality problem in smart grid and all the selected methods were to be compared after the results were obtained. The aim was to minimize network's technical losses, maintain levels of the voltage within the limits that are acceptable in network buses and to lower switching operations. That was achieved by using VRs and OLTC set tapping positions, and the state of SCs. The problem was transformed and became a multi-objective nonlinear optimization problem with equality and inequality constraints**(Paulo & Kagan, 2016).** However, the approach had its limitations, being the computational time respond needed to execute VVC optimization due to the extent of the problem search space. The VVC was evaluated using a trapezoidal membership function and the decision membership function, and it was determined by a group of membership functions associated with switching operations, voltage profile and power losses **(Paulo & Kagan, 2016)**. The following equation was determined:

$$\Upsilon_D = \Upsilon_J * \Upsilon^V * \Upsilon^S \quad (2.19)$$

where (Υ_J) is power lose membership function, (Υ_V) is voltage profile membership function, given by grades arithmetic mean for each bus and (Υ_S) is switching operations membership function, given by grades arithmetic mean for each switching equipment.

The formulation of VVC optimization problem was found by (Υ_D) maximum value or by objective function (f) minimum value, given by

$$\text{Min } f = 1 - \Upsilon_D \quad (2.20)$$

The problem was formulated in such a way that, taps for OLTC, Voltage regulator and status of the capacitor banks that minimizes the objective function f, needed to be found, subject to the constraints that are following:

The equation of the power flow was presented as follows:

$$g(P, Q, V, \delta) = 0 \quad (2.21)$$

P, Q is active and reactive power that is injected to the network buses.

$$V = [V_1, \ldots, V_i, \ldots, V_n]^t = \text{modules of bus voltage} \quad (2.22)$$

$$\delta = [\delta_1, \ldots, \delta_I, \ldots, \delta_n]^t = \text{angles of bus voltage} \quad (2.23)$$

Constraint of voltage level of the buses:

$$V_{min} < V_i < V_{max} \quad (2.24)$$

where V_{MIN} is the allowed minimum voltage, V_{max} is the allowed maximum voltage and V_i is bus i voltage.

Equations of constraints of equipment switching operations are as follows:

$$NS_{VRj} < LimS_{VR} \qquad j = 1, \ldots, N_{VR} \quad (2.25)$$

$$NS_{SCk} < LimS_{SC} \qquad k = 1, \ldots, N_{SC} \quad (2.26)$$

where NS_{OLTC} is the performance number of switching operations by OLTC, NS_{VRj} is the performance number of switching operations by VRj and NS_{SCk} is the performance number of switching operations by SCk in 24 hours. Lim_{SOLTC} is the switching operations daily limits for OLTC, Lim_{SVR} is the switching operations daily limits for VRs and Lim_{SSC} is the switching operations daily limit for SCs. N_{VR} is network's number of voltage regulators and N_{SC} is network's number of shunt capacitors**(Paulo & Kagan, 2016)**.

2.1.3. Study Previously done on other Evolutionary Algorithms

The three Evolutionary Algorithms being a Canonical Genetic algorithm, Memetic Algorithm, and Ant Colony Optimization were applied for the search of the solution using C++ tool. The Optimization of VVC was done on a distribution system with 13.8 kV, 2990 bus supplier, OLTC transformer and six shunt capacitors for seven controlling equipment. $\pm$5% to nominal voltage was the required voltage limit. Each algorithm ran 20 times for the optimization of the VVC, for the substation load curve with the highest demand and the result ware tabled showing the worst, best, average and success rate (SR) values of the objective function for each algorithm.

Table 2.1: SR values of the objective function for each algorithm(Paulo & Kagan, 2016).

Method	**Objective function values**				**SR (%)**
	Worst	Best	Average	Std. Dev.	
Canonical GA	0,6922	0,0000	0,1482	0,2075	20
GA variant	0,2000	0,0000	0,0215	0,0436	45
MA	0,0179	0,0000	0,0045	0,0077	75
ACO	0,1632	0,0000	0,0082	0,0356	95

However it was noticed that MA and ACO had a quick convergence to the best solution and MA took longer than other algorithms. 52 seconds was taken by MA to find the solution while 20 seconds was taken by ACO to find the solution**(Paulo & Kagan, 2016).** Taking Differential Evolution (DE) technique into account, a simulation was ran of Harmonic elimination PWM Method by Differential Evolution Optimization Technique. DE has been regarded as one of the most effective stochastic real-parameter optimization algorithm at present**(Vijayakumar1 & Devalalitha2, 2014)**.

2.1.4. Study Previously done on Differential Evolution

DE is regarded most effective because of its simplicity and efficiency which enables it to solving problems related to multi objective, dynamics and many other optimization problems. DE has three evolutionary functions, being mutation function, crossover function and selection function **(Gopal & Bansal, 2016).** Mutation function randomly generates variations to existing individuals to present new information into the population**(Ganbavale, 2014)**. Details of the functioning that creates mutation vectors $v_{i,g}$ at each generation g, based on the population of the current parent $\{X_{1,i,0} = (x_{1,i,0}, x_{2,i,0}, x_{3,i,0}, \dots \dots, x_{D,i,0}) | i = 1,2,3, \dots., NP\}$. The crossover function performs an exchange of information between different individuals in the current population. The final trial vector is formed by binomial crossover operation. The selection operator passes a driving force towards the most favourable point by preferring individuals of better fitness. The selection operation selects the better one from the parent vector $X_{i,}$ and the trial vector $u_{i,}$ according to their fitness values f (▪).

Table 2.2: DE optimized and unoptimized values(Vijayakumar & Devalalitha, 2014).

	unoptimized	optimized
1	231.9	234.38
5	2.36	0.01
7	6.65	0.01
11	7.4	0.04
13	15.49	0.05
17	9.84	0
19	2.68	0.01
23	7.5	0

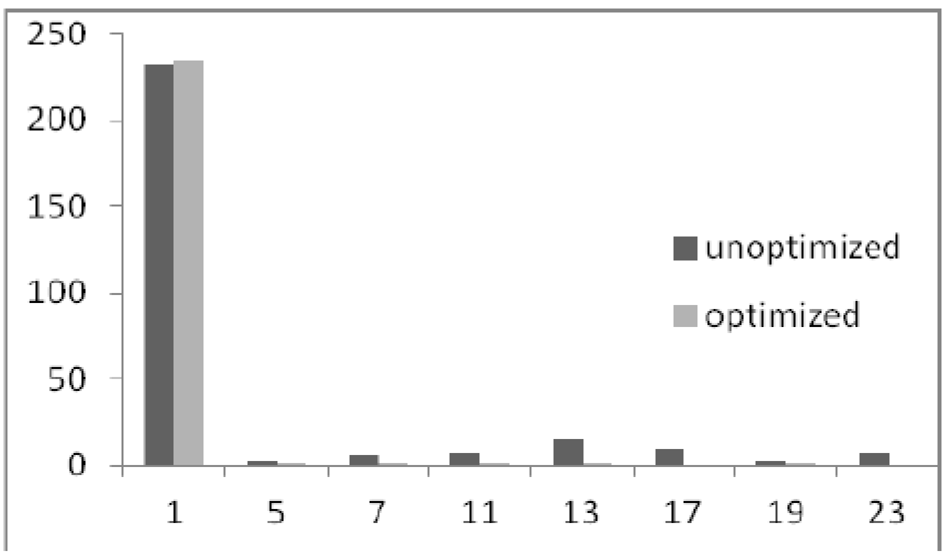


Figure 2.1: comparison of DE optimized and unoptimized values (Vijayakumar, et al., 2016)

The above Table 3 and Figure1 show the comparison of DE optimised and unoptimized simulated values of the 1st, 5th, 7th, 11th, 13th, 17th, 19th and 23rd Harmonics elimination in three phase voltage-source inverter. The aim of the research was to implement optimal switching strategies for harmonics elimination in the three phase voltage-source inverter using DE algorithm technique**(Vijayakumar & Devalalitha, 2014)**. The 5th, 7th, 11th, 13th, 17th, 19th and 23rd values of the optimized harmonics can be seen that they are approaching zero (0) compared to the unoptimized values. The declining in value of the above mentioned harmonics shows that the harmonics are eliminated in the three phase voltage-source inverter and that clearly shows the effectiveness of using DE algorithm technique for optimization problems.

Despite DE being regarded as the most effective global optimization algorithm, it has its own drawbacks. Many researchers have worked on improving DE to effectively solve global optimization related problems. One research was carried out based on improvement of DE for unconstrained optimization problems. It was reported that DE's rapid convergence and excellent capability of global search makes it more appropriate for parallel structure than conventional evolutionary algorithms**(Fang & Jie., 2016)**. With DE tendency of suffering from premature convergence, an improvement was proposed based on dynamic mutation and Opposition-based Learning Strategy (OBL). For new mutation function, Gaussian and Cauchy were major distribution functions of the random variable during the construction of new mutation operator. For OBL, its feasible solution and opposite direction solution were the main ideas when applied to optimal algorithm.

$$X^i = (x^i_1, x^i_2, \ldots, x^i_{ND}) \text{ search region feasible solution, where } x_j \in [a_j, b_j]. \quad (2.27)$$

$$x^{-i}_j = a_j + b_j - x^i_j \text{ defines opposite points.} \quad (2.28)$$

However, with numerical experiments, opposite elite solution proved to be more effective compared to ordinary solution. The table below shows the comparison between the results of Improved DE (IDE) and the ordinary DE. Symbol f denotes the benchmark functions used to evaluate the optimization effectiveness of the IDE algorithm**(Fang & Jie., 2016)**.

Table 2.3: comparison between DE and IDE results(Fang & Jie, 2016).

f	DE			IDE		
	Mean	*Std.*	*Wor.*	*Mean*	*Std.*	*Wor.*
1	30.26	12.63	83.05	9.27e-06	1.08e-05	4.79e-6
2	2.43	0.50	1.72	3.66e-13	1.67e-13	8.92e-13
3	0.01	0.01	0.07	0	0	0
4	26.49	4.27	37.85	0	0	0
5	0.01	0.01	0.03	1.20e-30	5.7e-29	2.89e-30

Analysis based on the numerical experiment above showed that IDE performs better than the standard DE for all the benchmark functions with local search ability and worse on global search ability. But IDE is able to balance the local and global search better the standard DE.

2.1.5. Study Previously done on Dynamic Voltage Restorer

Many researchers have worked on the power quality study and many solutions have been developed, one of them being a Dynamic Voltage Restorer (DVR). The DVR's main function discussed by many studies is to compensate voltage sag at times of fault occurrence. Power Quality Research Group at the Universiti Tenaga Nasional made a study on DVR solution for power quality and defined DVR as a power electronics device that compensates voltage sags by injecting three-phase voltage in series and in synchronism with the distribution feeder voltages**(Ramasamy, , et al., 2005).** However the results were not entirely satisfactory mainly because the method concentrated mainly on compensation of voltage sags during fault occurrence. Proposed was an improved DVR controller with two objectives, the first objective concentrating on voltage sags, while the second objective concentrating on voltage total harmonic distortion (THD). An improved and effective version of particle swarm optimization algorithm, namely a chaotic accelerated particle swarm optimization (CAPSO)) was used to determine the proportional integral controller coefficients of DVR. The coefficients were determined in a way that the main objective of optimization algorithm was considered as voltage sags and voltage THD was considered as its second objective. A suitable objective function was proposed for the optimization process by fuzzifying the objectives**(Shamsi-nejad, Khooban & Khalghani, 2014).** By comparison based on performance, a bi-objective PSO based controller showed an improvement since it involves both voltage sag and voltage THD problems as compared to the mono-objective type controller that focused only on voltage sags in terms of power quality indices. However, the results of the bi-objective optimization based DVR control study by **(Shamsi-nejad, Khooban & Khalghani, 2014)** suggested a great improvement to the DVR method of optimizing power quality. During the research, each object was defined in a membership function form in environment of fuzzy sets and they were then combined using appropriate weighting factors in a satisfactory fuzzy objective function form. Two objective functions linear combination formula for both voltage sags and voltage THD was developed.

$$F = -(w_1\, u_T + w_2\, u_D) \tag{2.29}$$

Where μ_T is voltage THD membership function and μ_D is sensitive load voltage sag membership function, w1 and w2 are weighting factors corresponding to μ_T and μ_D objects, respectively. Both objects have to convert to fuzzy membership function in order to have a better optimization performance. The results were obtained by simulation of the proposed solution on Simulink matlab and they were compared with the standard approach used before. The following results were obtained and compared.

Table 2.4: Different indices in both algorithms(Shamsi-nejad, Khooban & Khalghani, 2014)

	Minimum	Maximum	Average
standard PSO	−0.5747	−0.5361	−0.5602
proposed PSO	−0.583	−0.5693	−0.5749

It was concluded that the use of heuristic PSO algorithms achieved a better coefficients set for PI controller and the PI adjusted by the algorithms was said to be better than classical PI controller. It was also concluded that an improvement of the voltage sag and voltage THD was made by controller coefficients adjustment based on bi-objective optimization algorithm.

Another study on the power quality was conducted by **Amin Safari** and **Meisam Farrokhifar**. They suggested that Optimum Reconfiguration of network could help improve Quality and Reliability in Distribution System. In their study they also suggested that network quality level can significantly be increased by presence of distributed generation (DG). In this instance, number of generated voltage sags and the total number of interruptions were calculated by monitoring voltage magnitude of each bus for the test system. The simulation performed for the test results involved the distribution system of 33 bus test in absence and presence of distributed generations. The first mode was conducted in the absence of DGs in the network, for second mode, three DGs were present and allocated in the bus numbers of 10, 20 and 24. It was noticed that voltage profile can be directly affect by presence of distributed generations. The reconfiguration was done and it was noticed that the number of power interruptions had better condition to the customers after reconfiguration even at the presence DGs to the grid. It was concluded that reconfiguration of network can develop distribution network, but network reconfiguration can significantly enhance distribution system indices in presence of distributed generations **(Amin Safari, Meisam Farrokhifar, 2016).**

Most researchers have concentrated mainly on the compensation of under-voltage being the main function of the voltage quality problem. However only few have touched the compensation of over-voltage and that being the voltage swell type of the over-voltage which is said to be 10% over voltage**(Hafezi & Faranda, 2016).** Other over-voltage types such as voltage surges and voltage spikes have been ignored in researches of voltage quality and they also contribute to the poor voltage quality supplied to the consumers. Voltage surges and voltage spikes which are primarily caused by lightning strikes are difficult to ignore as they can cause a serious damage to the household's appliances and equipment. An improvement of a single Multi-Objective Voltage and Power Quality Optimization regulating method will be researched and developed that will control and optimize the delivered voltage and power to the best quality standard required by the end-users using the Differential Evolution with the first function being the compensation of under-voltage such as voltage sags, the second function being the reduction of the over-voltages to the required set point voltage and the third function being the mitigation of the extra over-voltages such as voltage spikes and voltage surges in the distribution section of the smart grid.

2.2. Theory contributing towards the research

2.2.1. Smart grid overview

The whole world has a common goal to archive in electrical power field, economical sustainable, flexible and efficient power supply to the society. Smart Grid being the solution to that, researchers from across the globe have gathered and are working together to archive Smart Grid, the solution to a dynamic supply of electricity**.** Smart Grid involves different techniques and different technologies, and each technique performs in a distinct manner and symmetry, depending on commercial attractiveness, and local needs, therefore leading to smart grid not having a universal definition **(Capriglione, et al.,**

2016). Different visions for smart grid technology have been aligned by researchers, organizations and institutions. Here are some of the smart grid visions by researchers and institutions, smart grid communications vision, smart grid Renewable energy resources, Smart Grid Automation and Controls technology vision.

2.2.2. Smart Grid vision on communications

With communication being one of the key components in smart grid's vison **(Gungor & Hancke, 2010)**, the IEEE lays out three basic aspects to be considered in Smart Grid's communication network. Space, time and entropy are three basic communication features. Space is the distance over which information must be communicated. Time is the period taken for information to be transported to its destination over that distance. Entropy is a measure of complexity, which in this case refers to transmission of information and electricity **(Bush, 2013)**. The architecture of the electric power grid and its supporting communication network are reciprocally related. Power grid applications that are unable be handled by local control are supported by Communication network, and this relationship drives the communication model in smart grid. According to **(Bush, 2013),** space in communication is defined by the following acronyms and illustrated by Figure 2.2 bellow.

• **HAN**: Home Area Network, relates to power consumption.

• **NAN/FAN**: Neighbourhood Area Network/Field Area Network. Relates to power generation and consumption.

• **MAN**: Metropolitan Area Network. Relates to power distribution.

• **WAN**: Wide Area Network. Relates to power transmission.

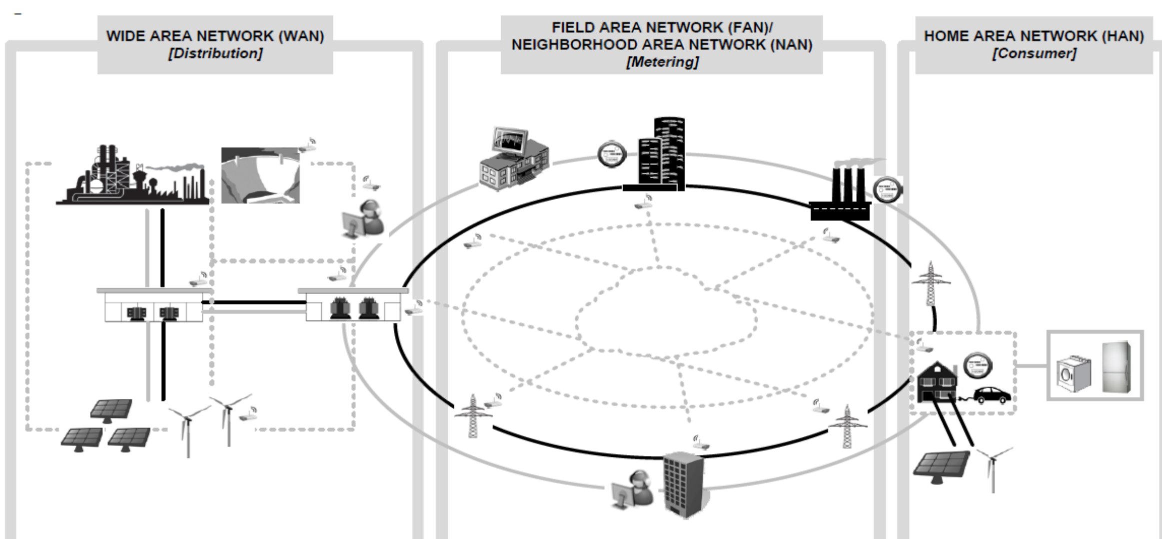


Figure 2.2: Communication network illustration with regards to space in Smart Grid (Bush, 2013).

Time is very important for control stability and it is related to transmission of signal as well as message length and transmission frame. Time in communication network is Influenced by unite size of protocol data and packetization delay, as well as by arranging delays into a queue along the path **(Bush, 2013).**

Entropy is associated with measurement of power grid complexity and the corresponding of information volume that is communicated. Based on **(Bush, 2013)**, an increase in electric power grid complexity requires an increase in communication network throughout and in the beneath capacity of channels for sufficient support of control system of the Smart Grid. the information that is needed to be communicated by the control system becomes harder to compress as the parameters of power of interest become less reciprocally related, and at the extreme situation of completely decorrelation of parameters, the distributed stochastic control system will require infinite bandwidth for communication and therefore becomes uncontrollable**(Bush, 2013)**.

Wired and wireless are two main communication media used to transmit data in the communication network and they support different communication technologies that can be used in Smart Grid. However there are advantages and disadvantages between these communication media. For instance wireless medium has freedom of connection to difficult or unreachable areas and low-cost infrastructure. On the other hand the transmission path nature of wireless medium may cause the signal to go weaker as the connection distance increases and their functions depend on batteries often. For wired medium, their functions are independent of batteries and they don't experience signal interference problems, however their infrastructure is costly and sometimes it is difficult for them to reach other locations **(Gungor, et al., 2011)**. With information flow required from sensor and electrical appliances to smart meters, and from smart meters to utility's data centres, the following communication technologies can be used in Smart Grid: Zigbee, Wireless Mesh, Cellular Network Communication, powerline Communication and Digital Subscriber Lines.

a. **ZigBee** is a wireless communications technology that uses proportionately low power, data rate, complexity, and deployment cost **(Gungor, et al., 2011)**. It is the most suitable technology for home automation, energy monitoring, smart lightning, and automatic meter reading. According to **(Peizhong, Iwayemi, & Zhou, 2011)**, ZigBee and ZigBee Smart Energy Profile (SEP) have been realized as the most suitable communication standards for residential network of Smart Grid domain by the U.S. National Institute for Standards and Technology (NIST)**.**

b. **Wireless Mesh network** is a composed set of nodes flexible network, where new nodes can join the group and each node can behave as an independent router. The characteristic of self-healing of the network activates the communication signals to find another route via the enabled nodes, in case any node drops out on the network **(Gungor, et al., 2011)**.

c. Existing **cellular network technology** can be an excellent option for communication between power utilities and smart meters and between far nodes. Based on **(Gungor, et al., 2011),** the existing communications infrastructure can make power utilities to avoid additional operational costs and time for building a dedicated communications infrastructure. Cellular network solutions also enable deployments spreading of smart metering to a wide area environment. The available cellular communication technologies to utilities for smart metering deployments are 2G, 2.5G, 3G, WiMAX, and LTE.

d. **Powerline communication** (PLC) is a technique that transmits high-speed (2–3 Mb/s) data signals from one device to the other using the existing powerlines **(Gungor, et al., 2011)**. Due to the successful implementations of AMI in urban areas where other solutions struggle to meet the needs of utilities and direct connection with the meter, PLC has been the first choice for communication with the electricity meter **(Lewis, Igic & Zhongfu, 2009)**.

e. Digital Subscriber Lines (DSLs) is a digital high-speed data transmission technology that makes usage of the voice telephone network wires. Frequencies greater than 1 MHz are commonly seen through an ADSL enabled telephone line **(Laverty, et al., 2010**). Installation costs are reduced by the already existing infrastructure of DSL lines. For this reason, many companies chose DSL technology for their smart grid projects **(Gungor, et al., 2011)**.

Below Figure 2.3 demonstrates the Communication network infrastructure for smart grid optimization with regards to communication.

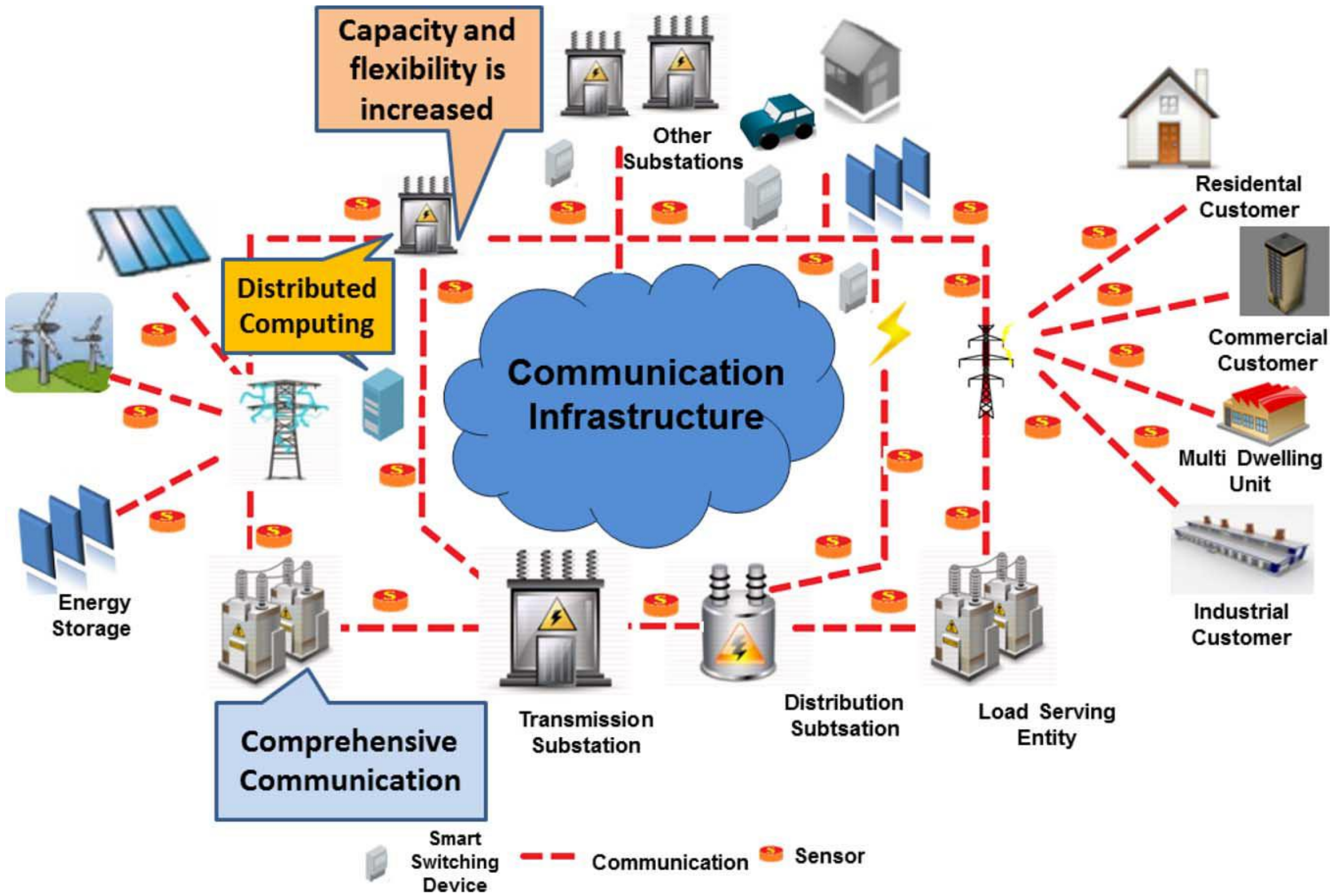


Figure 2.3: Smart Grid communication Infrastructure (Gungor, et al., 2011).

2.2.3. Smart Grid Automation and Controls technology vision

Control systems and automation technology are the most influential components in Smart Grid's vision of delivering economical and efficient power to the consumers. Control technology is driven by technical components such as sensors, actuators, computing Algorithms, user interfaces and communications. New opportunities for application of control concepts, theory, and algorithms are brought forward by improvements in all of these areas **(Samad & Annaswamy, 2017).** In Smart Grid, human effort is reduced by use of software algorithms which can process the data faster, non-stop and perform control actions on behalf of the humans. Sophisticated control algorithms use the exchange of information on the communication links to generate control action which fulfils several economical and operational constraints in Smart Grid (**Khanna, 2012)**. Following the review of control elements mentioned above.

a. **Sensors and Instrumentation**

Smart metering is one example of sensors and instrumentation and it is deployed for automated meter reading at remote side away from the utility. It is an improvement from manual meter reading where personnel had to physically access installed meters. Smart meters are used to measure power consumption by consumers and are installed in customer facilities such as residential, small commercial buildings and industrial business locations **(Samad & Annaswamy, 2017)**. Another important measurement development is **Phasor measurement units (PMU).** PMUs measure electrical wave data from transmission lines on an electrical grid using a common time source for synchronization. The synchronous real timestamps compares current and voltage values at different points on the grid **(Samad & Annaswamy, 2017)**. Waveform data is transmitted with microsecond-accuracy timing and at frequencies that are multiples of the line frequency (50/60 Hz). Home automation hubs that integrate energy, security, entertainment, and other functions and can serve as sensors for associated parameters **(Samad & Annaswamy, 2017)**.

b. **Actuation**

Actuation involves control of automated mechanism which can make effective changes on the power grid. Example of actuation is control of active power which is achieved by adjusting generator to balance the power grid, as well as for auxiliary services such as regulation of frequency **(Samad & Annaswamy, 2017)**. **Smart Inverter** is one of the most important components in actuation. Inverters convert DC power from solar photovoltaic systems into AC power which is fed to the Smart Grid for transmission and distribution to the consumers. Smart inverters provide intensified communication and control functions, bringing more flexibility and intelligence for conversion and injection of reactive power. Another example of actuation is **FACTS devices** such as **reactors** and **capacitor banks** which are used for control of flow of electricity in transmission lines. Modern developments have resulted in intensified capabilities of control through real-time reactive power injection and absorption control, furnishing opportunities for distributed voltage and frequency control **(Samad & Annaswamy, 2017)**. **On-load tap changers, switched capacitors**, and **static VAR compensators** are examples of additional actuators that provide capable response over a wide range of time constants, ranging from milliseconds to minutes **(Annaswamy, 2013).**

c. **Computational Platforms**

Advanced control algorithms, computational hardware, Operating Systems and web browser are all examples of computational platforms due to the fact that a program code is executed for them to operate their duties. Computational platform place a very important role is control system of the Smart Grid by automating systems through coding. Computational platform require suitably capable processors for execution and their computational speeds depend on the scale and complexity of the problem. Computational hardware has improved across the grid, from system operators to utilities to consumers **(Samad & Annaswamy, 2017)**.

2.2.4. Smart Grid Renewable Energy Sources vision

The aim of Smart Grid vision on renewable energy sources is to achieve a greenhouse gas free electric power, economical, efficient and flexible power that is able to supply remote side areas such as rural areas. Therefore, the use of distributed renewable energy sources such as solar and wind is the best solution to clean, sustainable and affordable electric power in societies. Different countries are encouraging generation of electricity by renewable energy sources in order to decarbonize the power generation **(Kanjiya & Khadkikar, 2013)**. Smart grid technologies enable high levels of renewable energy sources to be included in an electrical power system and it offer benefits such reduced operational costs and a more efficiently operated electricity system **(Atasoy, Akinç & Erçin, 2015)**. Energy storages are integrated as part of renewable energy source technology in smart grid. According to **(Atasoy, Akinç & Erçin, 2015)** review, Energy storage can be integrated at different levels of the electrical system in smart grid vision. Following are the levels energy storage can be integrated on:

- Generation level: Arbitrage, balancing and reserve power, etc.
- Power Grid level: voltage control, frequency control, capacity support, investment deferral, etc.
- End-user level: peak shaving, cost management, etc.

Wind generation is one part used for integration of renewable energy sources. With its nature of using wind for electricity generation, it achieves cheap and clean generation of electricity to smart grid. The output electricity of wind turbines depends on the wind kinetic energy. The speed of the Wind fluctuates greatly in a short period of time, which determines the great fluctuation of wind power output in the short period of time. Wind fluctuations are very low in seasonal and annual periods, and the output of wind electric power has the statistical properties in the long term **(Zhang, et al., 2017)**. For efficient generation of electric power, the amount of air entering the turbine must be equal to the amount of air leaving the turbine. According to Betz's law, a maximum of wind power is achievable with 59.3% of the total kinetic energy of the air flowing through the turbine **(Grogg, 2005)**.

Solar energy is one of the most favourable renewable energy resources for bulk power generation for smart grid application. In this case solar energy is converted into electric power by means of photovoltaic cells **(Wan, et al., 2015).** Photovoltaic power generation has introduced significant environmental and economic interests to the public social awareness, such as carbon dioxide emissions reduction **(Hosenuzzaman, et al., 2015)**. Photovoltaic system is made up of arranged solar panels to absorb and convert photons into electricity, inverter to convert DC voltage to AC voltage, as well as supporting cabling and other auxiliary electrical components to put together an operational system **(Okwu, et al., 2017)**. Photovoltaic system may also employ a system for solar tracking to intensify the system's overall performance and include charge controller, which is an integrated battery solution **(Okwu, et al., 2017)**. Following Figures illustrates Photovoltaic system.

Figure 2.4: Photovoltaic Solar panels (Okwu, et al., 2017).

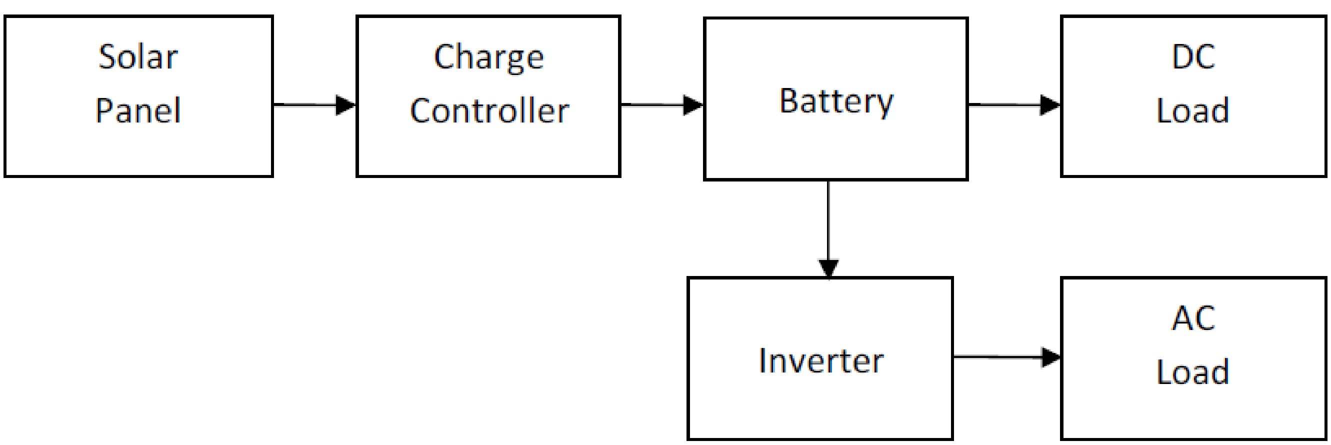


Figure 2.5: Block diagram for Photovoltaic solar system (Okwu, et al., 2017).

2.3. Power problems in Smart grid

It is difficult to discuss and study power quality problems, this is because of different terminologies used to describe existing power disturbances, and that creates more confusion in attempting to solve power quality issues. The Institution of Electrical and Electronic Engineers (IEEE) tried to address the issue of using different terminologies by developing standards that include definition of power disturbance. The general definition of power disturbance states that, power disturbance is any interruption of voltage, current or frequency that opposes normal operation of the power system (**Seymour & Horsley, 2008**).Poor power quality causes malfunction and overheating of electrical equipment, power supply failure that results in blowing of fuses and tripping of circuit breakers, damage to sensitive equipment such as computers and production line control systems and interferences of electronic communications to name few. Such occurrences result in system outage, inefficient running and a reduced life span of electrical installations. Eventually that result in high running costs of installations, leading to the production being stopped and major costs being incurred (**Schipman & François Delincé, 2010)**. Following are types of power quality problems encountered in power grid.

a. **Transients**

There are two types of transient disturbances, impulsive and oscillatory. **Impulsive transient** is a sudden extra-rise of voltage or current above normal operational voltage or current level that occurs unidirectional in polarity (either positive or negative) **(Dugan, et al., 2004)**. It is categorised by its speed of occurrence on the event of disturbance. Impulsive transients can rise within 5 ns (nanoseconds) from steady state to the peak of the impulse. Impulsive transients are normally caused by Electrostatic Discharge, poor grounding, lightning, utility fault clearing and switching of inductive loads. Other terms used to refer to impulsive transients are, surges and spikes. The occurrence of impulsive transient can cause data loss or corruption to PCs and control instrumentation for production lines and physical damage to equipment (**Seymour & Horsley, 2008**).

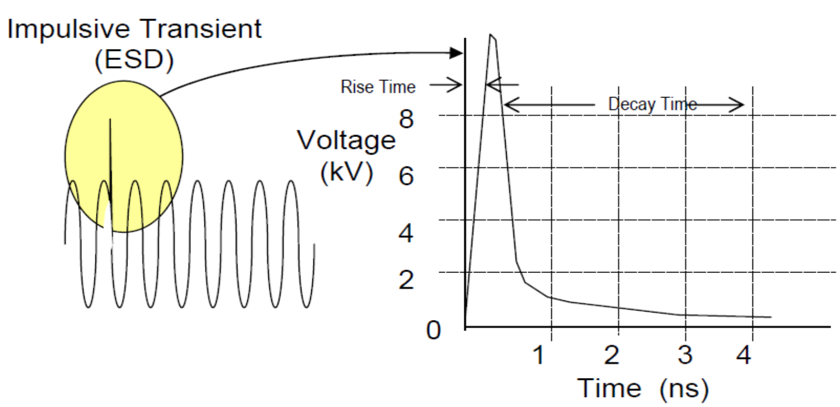


Figure 2.6: Positive impulsive transient (Seymour & Horsley, 2008).

Oscillatory transient is a sudden variation in voltage and current's steady-state condition of the signal at unidirectional limits (either positive or negative), oscillating at the frequency of the natural system. Oscillatory transient makes the signal of the power to alternately rise and then shrink very fast **(Seymour & Horsley, 2008)**. Oscillatory transients occur when capacitive and inductive loads such as capacitor banks and motors are turned off. Oscillatory transients can cause disruption to electronic equipment and a rise in the dc link voltage of the adjustable speed drives, resulting in tripping of the adjustable speed drives. According to **(Seymour & Horsley, 2008)**, transient disturbances cause most damaging to household and industrial electrical equipment and appliances. Transient Voltage Surge Suppressors (TVSS) such as metal oxide varistor (MOV) are normally used to overcome the impulse transients while line reactors and chokes are used to overcome oscillatory transients.

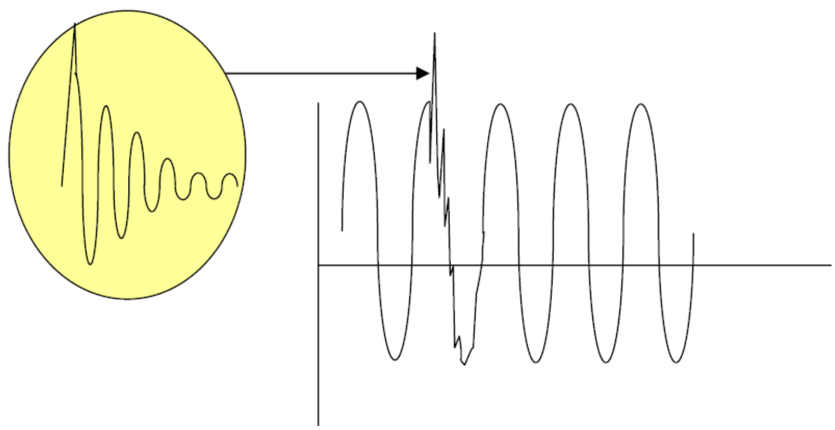


Figure 2.7: Oscillatory transient caused by automatically switching in capacitor banks (Seymour & Horsley, 2008).

b. Power interruptions

Power interruption is a complete loss of power supply to a particular location and it has four categories, depending on duration of occurrence. The first one is instantaneous interruption which lasts from 0.5 to 30 cycles, momentary interruption lasts from 30 cycles to 2 seconds, while temporal interruption lasts from 2 seconds to 2 minutes and sustained interruption takes more than 2 minutes until power is restored, depending on the fault sustained in the power grid banks **(Seymour & Horsley, 2008).** There are many causes of power interruptions in the society and industries, but most come as a result of power supply grid damage caused by lightning strikes, destructive weather(high winds, heavy snow or ice on lines, etc.), equipment failure, animals, trees, , basic circuit breaker tripping and vehicle accidents. Another cause of power interruption in the commercial power systems is protective devices such as automatic circuit reclosers. Power interruptions can result in disruption, damage to equipment, and downtime to homes industrial places. Power interruptions can also cause loss of valuable data in business computer due to corruption of information during power interruption and product ruination during downtime and that can result in cost losses in production companies. Good design and frequent maintenance of utility systems can reduce power interruptions in industries and communities. Other solutions to power interruptions are employing mitigating devices such as motor generator and uninterruptible power supply (UPS) **(Seymour & Horsley, 2008)**. Other terms associated with power interruptions are, power outage, power cut, power out, power failure and power blackout.

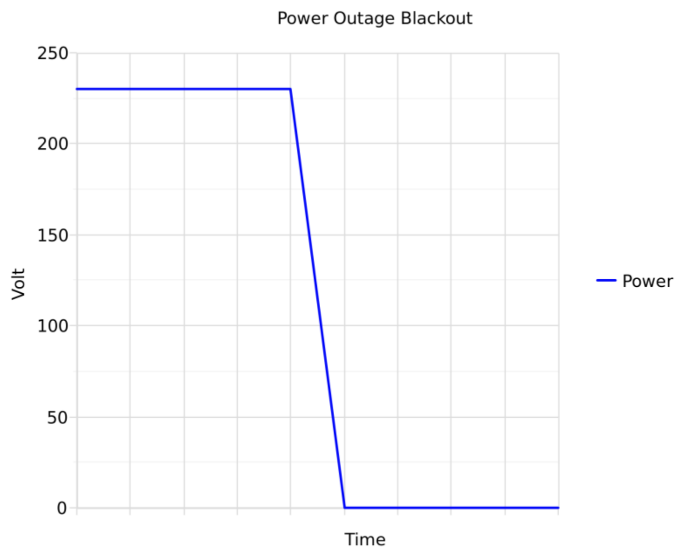
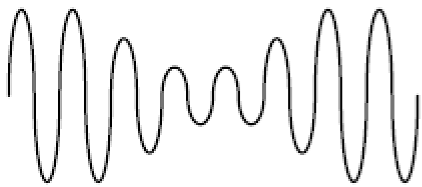


Figure 2.8: Sustained power interruption (Liftarn (talk), 2009)

c. Voltage Sag / Under-voltage

Voltage sag is defined as a reduction of the operational voltage level between 10 to 90% of the root mean square voltage, for the duration of 0.5 cycle to 1 min **(Anand, Mahamadnayeem & Atre, 2014), (Thakur & Singh, 2017)**. Voltage sags are usually caused by switching on loads with heavy start-up currents such as industrial motors which can draw six times or more of its normal running current while starting, causing a great voltage dip to the rest of the circuit it resides on. Voltage sags cause damage to equipment, data corruption in industrial computers and errors in industrial processing production lines **(Seymour & Horsley, 2008)**. Voltage sags can be mitigated by providing alternative power starting sources separate from the one that loads sensitive electrical equipment for heavy loads and loads with heavy start-up currents. UPS equipment, motor generators, and system design techniques can also mitigate voltage sags. Under-voltages come as a result of long-term problems that cause sags. Under-voltages can cause overheating in motors, and can lead to the failure of loads that are nonlinear such as power supplies of computer. Solutions for voltage sags also apply to under-voltages.



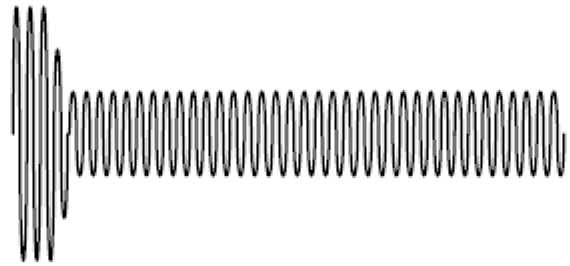
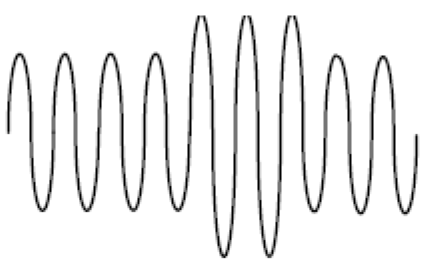


Figure 2.9a: voltage sags(Seymour & Horsley, 2008). **Figure 2.9b: under-voltage(Seymour & Horsley, 2008).**

d. **Voltage Swell / Over-voltage**

Voltage swell is the reverse form of voltage sag, swell is defined as the increase of the root mean square voltage level from 110% to 180% above the operational voltage level with duration of more than 3 cycles **(Thakur & Singh, 2017)**. Voltage Swells are caused by switching-on heavy or reactive equipment such as motors, transformers, motor drives or power factor correction equipment **(Edomah, 2009).** Other causes of voltage sags are sudden reductions of large loads, single-phase fault on a three-phase system as well as high-impedance neutral connections **(Seymour & Horsley, 2008).** Voltage swells can cause lights flickering, data errors, degradation of electrical contacts and insulation and semiconductor damage in electronic equipment. Solutions for Voltage sags mitigation are UPS systems, ferroresonant control transformers and power line conditioners. Over-voltages are extension of voltage swell and they come as a result of long-term problems that cause voltage swells. Solutions for voltage swells also apply to over-voltages.



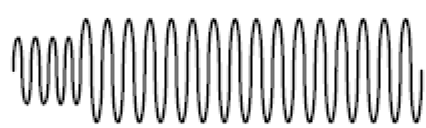


Figure 2.10a: Voltage swells(Seymour & Horsley, 2008). **Figure 2.10b: Over-voltage(Seymour & Horsley, 2008).**

e. **Waveform Distortion**

There are five categories for waveform distortion disturbances, DC offset, Harmonics, Inter-harmonics, Notching and Noise. **DC offset** are induced direct currents and voltages in ac distribution systems and they come as a result of failure of rectifiers within the many ac to dc conversion technologies that have rapidly increased modern equipment. DC offsets can cause instability in electronic load equipment, overheating and saturation of transformers, resulting in transformer not being able to deliver full power to the load. DC offset in the system can be mitigated by replacing the faulty equipment that creates dc offset problem **(Seymour & Horsley, 2008)**.

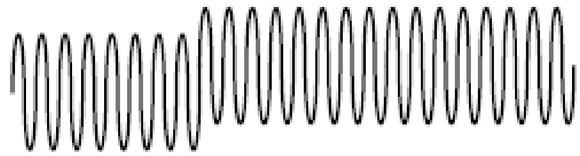


Figure 2.11 DC offset(Seymour & Horsley, 2008).

Harmonic distortion is the fundamental sine wave corruption at frequencies that are multiples of the fundamental. Harmonic distortion is caused by transformer overheating, neutral conductors, circuit breaker tripping and loss of synchronization on timing circuits that are dependent upon a clean sine wave trigger at the zero crossover point. Harmonic distortions are mitigated by installing harmonic filters, K-rated transformers and over-sizing the neutral conductors.

Figure 2.12: Harmonics distortion waveform(Seymour & Horsley, 2008)

Inter-harmonics come as a result of forced signal on the voltage supply by electrical equipment such as induction motors, static frequency converters and arcing devices. Inter-harmonics cause visual flickering of incandescent lights and displays and they can also cause possible heat and communication interference **(Seymour & Horsley, 2008)**. They can be mitigated by UPS systems, filters and line conditioners**.**

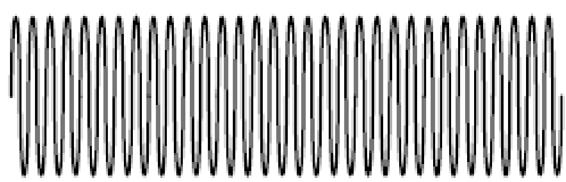


Figure 2.13: Inter-harmonics waveform distortion(Seymour & Horsley, 2008).

Notching is defined as a periodic disturbance of voltage and it is caused by electronic devices such as light dimmers, variable speed drives and arc welders under normal operation. Notching is mitigated by UPSs and filter equipment.

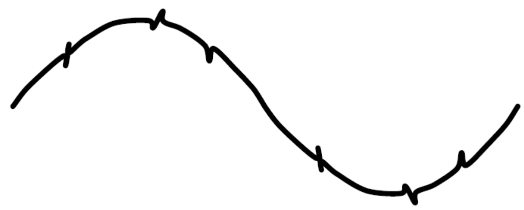


Figure 2.14: Notching waveform(Seymour & Horsley, 2008).

Noise is defined as unwanted current or voltage superimposed on the power system current or voltage waveform. Noise is caused by control circuits, power electronic devices, switching power supplies, arc welders and radio transmitters. Noise can cause equipment malfunction, data errors, long-term component failure, hard disk failure and distorted video displays. Noise can be mitigated by Isolating the load via a UPS, install a grounded and shielded isolation transformer, relocating the load away from the interference source, installing noise filters, cable shielding **(Seymour & Horsley, 2008).**

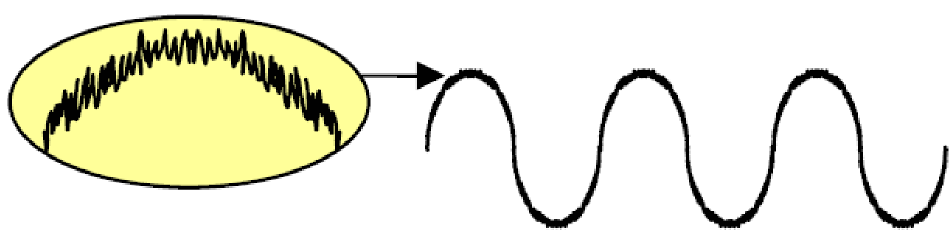


Figure 2.15: Noise waveform(Seymour & Horsley, 2008).

f. Voltage Fluctuations

A Voltage fluctuation is defined as a systematic change of the waveform of voltage or a series of random variations of small measurable voltages, namely 95 to 105% of nominal at a low frequency below 25 Hz**(Seymour & Horsley, 2008)**. Voltage fluctuations are caused by load exhibiting current variations and arc furnaces on the transmission and distribution system. They can cause flickering of incandescent lamps. Solutions to voltage fluctuations could be relocation of sensitive equipment, removing the offending load and installing power line conditioning and UPS devices.

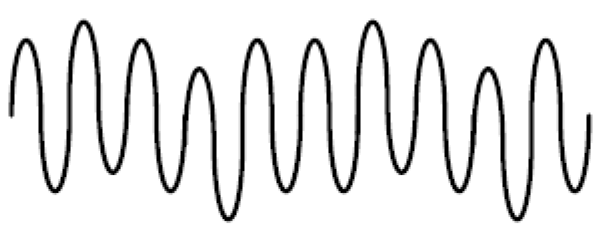


Figure 2.16: Voltage fluctuations(Seymour & Horsley, 2008).

g. **Frequency Variations**

Frequency variation can be experienced in poor power infrastructure and situations where generator is heavily loaded and can cause a motor to run slower or faster to synchronise the input power frequency. Frequency variations cause inefficient running of the motor and can lead to excessive degradation of the motor and more heating of the motor through razed motor speed and additional current draws. Mitigation for frequency variation can be done by repairing, correcting or replacing power sources causing the frequency variation **(Seymour & Horsley, 2008)**.

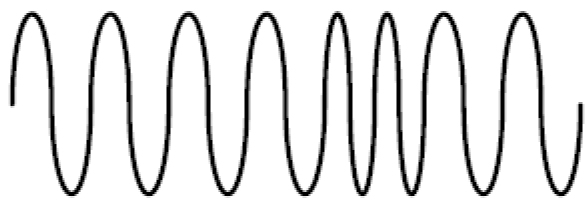


Figure 2.17: Frequency variations(Seymour & Horsley, 2008).

2.4. Dynamic Voltage Restorer

Researchers have developed many solutions to overcome poor power quality on society and industries. However the most commonly used solution is dynamic voltage restorer (DVR) due to its high efficiency and fast response. A DVR is a power electronic device that is employed to inject a dynamically controlled voltage in series and in synchronism with the operational voltages for voltage sag and swell compensation and that helps to regulate the load voltage profile during the voltage quality events and allows control of real and reactive power exchange between the DVR and the distribution system **(Brumsickle, et al., 2001), (Ramasamy, et al., 2005)**. DVR is mostly installed in a distribution system, located between the power supply and the sensitive load feeder at the point of common coupling (PCC) and it can be considered as a variable or controllable voltage source **(Jena, et al., 2011)**. Figure 2.18 shows the location of the DVR in the distribution system.

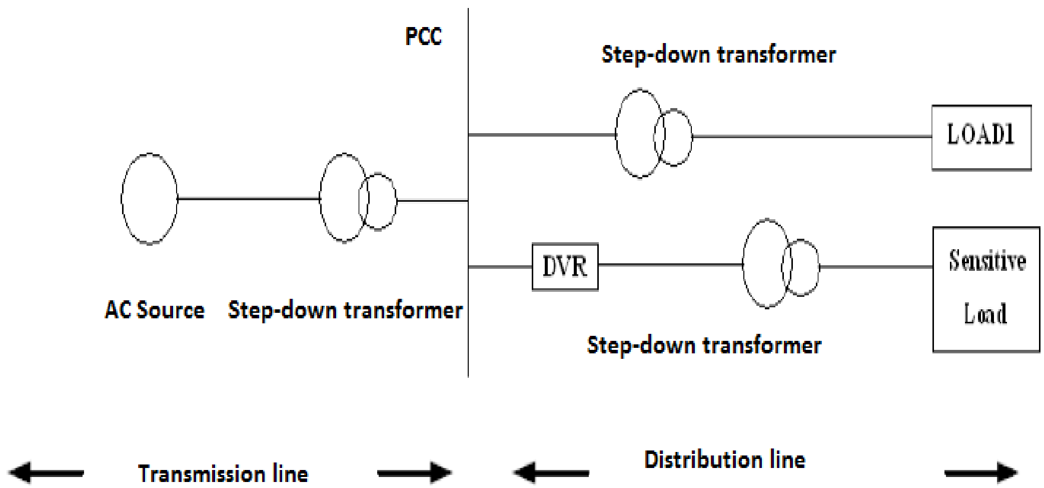


Figure 2.18: DVR location in Power system**(Jena, et al., 2011).**

DVR consists of four major parts.

a. The first part is Voltage Source Inverter (VSI). VSI converts the direct current (DC) voltage it collects from the Storage unit to Alternate Current (AC) voltage before it passes the transformer unit. VSI has a high current ratings and low voltage ratings hence step up transformer is employed to boost the voltage injected **(Ramasamy, et al., 2005)**.

b. The second part is Injection Transformers. Injection Transformer is connected between the VSI AC terminals and the passive filters. Their main purpose is to inject the inverted AC voltage to the sensitive load in order to compensate voltage sags or impose voltage swells towards the sensitive load.

c. The third part on DVR is Passive Filters. Passive filters are located at the high voltage side of the injection transformers to filter harmonics **(Ramasamy, et al., 2005)**.

d. The forth part of the DVR is Energy storage. Batteries, flywheels and Superconducting Magnetic Energies can be used to provide real power for compensation as it is necessary when large voltage sag occurs **(Ramasamy, et al., 2005)**. Figure 2.19 shows DVR schematic diagram.

e. The fifth part is the circuit of dc charger which is allocated two main duties, the primary duty is to recharge the energy source after the event of voltage sag compensation, and the secondary duty is to keep a continuous voltage of the dc link at the nominal dc link voltage level **(Jena, et al., 2011)**.

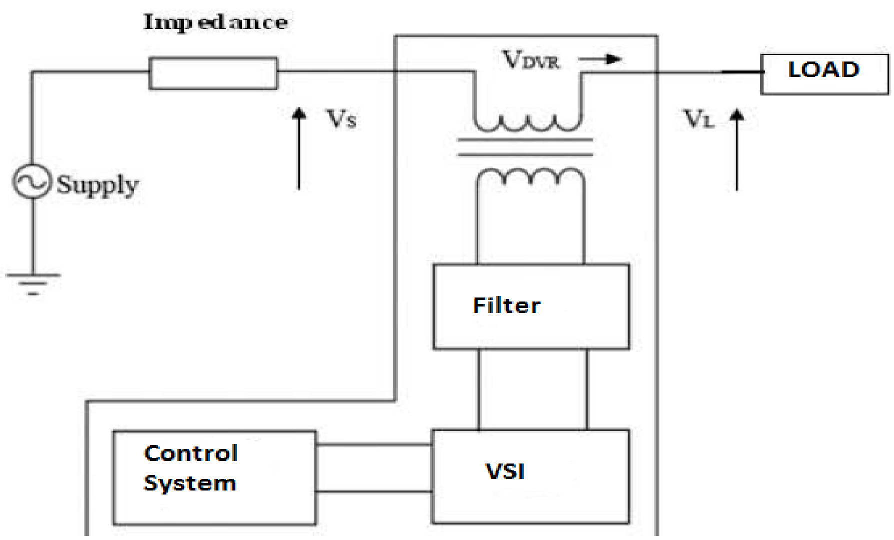


Figure 2.19: DVR schematic Diagram (Ramasamy, et al., 2005).

The main objective of the DVR is to inject a dynamically controlled voltage V_{DVR} generated by a forced commutated inverter in series to the bus voltage by means of the injection transformer **(Jena, et al., 2011)**. Following Figure 2.20 is the equivalent DVR circuit diagram.

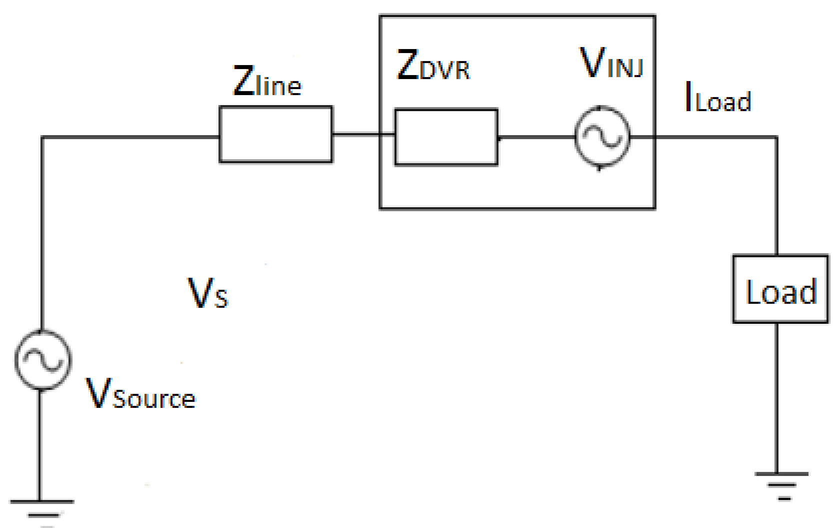


Figure 2.20: Equivalent DVR circuit diagram**(Jena, et al., 2011).**

Following are DVR voltage compensation formulas according to **(Jena, et al., 2011),**

$$V_{DVR} = V_L + Z_{TH}I_L - V_{TH} \tag{2.30}$$

where

V_L = the desired load voltage magnitude.

Z_{TH} = the load impedance.

I_L = the load current.

V_{TH} = the system voltage during fault condition.

The Z_{TH} impedance of the system depends on the load bus fault level. When the V_{TH} voltage of the system drops, DVR injects V_{DVR} series voltage from the VSI through injection transformer, to maintain V_L the desired load voltage magnitude.

The load current can also be expressed in the below form:

$$I_L = (P_L + jQ_L)/V \tag{2.31}$$

If V_L is placed as a reference, then the formula can be written as,

$$V_{DVR}\angle 0 + V_L \angle 0 + Z_{TH} \angle(\beta - \theta) - V_{TH} \angle\delta \tag{2.32}$$

$\propto, \beta, \delta$ are angles of V_{DVR}, Z_{TH} and V_{TH} respectively. θ is the load power angle and can be obtained by the following formula,

$$\theta = tan^{-1}(\frac{Q_L}{P_L}) \tag{2.33}$$

where Q_L and P_L is load reactive and active power respectively.

The complex power injection of the DVR can be written as,

$$S_{DVR} = V_{DVR}I_L^{*} \tag{2.34}$$

During DVR operation, V_{DVR} is equals to Zero ($V_{DVR} = 0$) when there is no fault being experienced on the sensitive load, therefore the mode is standby mode. Whenever the sensitive load experiences the fault, DVR senses the voltage magnitude difference through the control system and it would inject the correct amount of voltage level to compensate or to superimpose the fault on the sensitive load. Therefore the mode is injection/boosting mode ($V_{DVR} > 0$).

2.4.1 DVR Compensation Techniques

There are different techniques of compensation in DVR employed to maintain constant load voltage depending on the type of load – whether it is phase sensitive, magnitude sensitive, or both. The study and analysis of reaction of the load to magnitude change, phase disturbance or both is required and compensation method is selected based on reflection of disturbance as more severe and critical on the load **(Remya, et al., 2018)**. Different voltage injection methods are discussed below.

In-phase Voltage Compensation Technique

The technique of in-phase voltage compensation is the most suitable method for sensitive loads magnitude. Without considering the pre-fault conditions, it restores the load voltage by injecting the lost voltage in phase with the supply voltage **(Buxton, 1998).** Since the compensated voltage is in phase with the supply voltage, the energy storage for active power compensation required. According **(Remya, et al., 2018),** this technique does not address the phase jumps. Both real and reactive powers are involved in load voltage restoration during in-phase compensation **(Remya, et al., 2018)**.

Pre-sag Compensation Method

Pre-sag compensation technique is used in order to compensate both phase jumps and magnitude. The complementary voltages of nature in magnitude, harmonics and wave shape are injected by the DVR to compensate the difference between the pre-fault and fault voltage **(Remya, et al., 2018)**.The load voltage after and before fault is in synchronize with both magnitude and phase. This technique is suitable for balanced and unbalanced sags with or without phase jumps **(Meyer, 2008)**. The technique also ensures large voltage injection capability. For this compensation method, large energy source storage is required to supply the active and reactive power to the inverter **(Remya, et al., 2018).**

Energy Minimized Compensation Method

According to **(Remya, et al., 2018),** the type of voltage disturbance and the type of compensation technique gives indication to which amount of real and reactive power required by the DVR for compensating a particular disturbance. The compensation of zero active power is achieved by injecting the voltage in quadrature with the current of the load **(Danbumrungtrakul, et al., 2017)**. For this technique, the energy storage capacity is reduced and the reduction is inversely proportional to the depth of the sag. According to **(Chiang, et al., 2005)**, this technique is not suitable for sensitive loads sag mitigation with high power factor **(Remya, et al., 2018)**.

2.5. Multi-Objective Optimization

Multi-objective optimization is a procedure that minimizes or maximizes objectives that are under imposed constraints. It is a mathematical or algorithmic tool that is characterized by two or more objectives **(Adekoya & Helbig, 2017).** In multi-problem optimization, two or more objectives are usually on conflict, therefore the evolutionary algorithm are required to search the best optimal solution**(Reyes-Sierra & Coello, 2006)**. Different multi-objective strategies have been applied to the problems where the correct clustering solution corresponds to a trade-off between two or more clustering metrics**(Lezama, Rodrıguez-Gonz´alez & de Cote, 2016).** One strategy used in multi-objective optimization is Pareto Front. Pareto front is the set of all Pareto efficient allocations, conventionally shown in graph. It allocates resources from an impossible situation, making one individual or preference criterion best optimal without making individual or preference criterion worse optimal**(Chaves-Gonz´alez & P´erez-Toledano, 2015)**. Pareto front is represented by Pareto-optimal solutions. The measure of performance of the multi-objective problems depends on a well dispersed set of optimal solutions in the Pareto Front **(Suganthi, et al., 216)**. A multi-objective problem can be mathematically formulated as follows:

Minimize $F(x) = [\, f_1(x),\ldots,f_m(x)\,]$

Subject to:

$$g(x) = 0 \qquad j = 1,\ldots M \tag{2.35}$$

$$h(x) = 0 \qquad k = 1,\ldots,K \tag{2.36}$$

where

$F(x)$ is made up of m conflicting objective functions,

x = the decision vector,

g_j = the j^{th} equality constraint

h_k = the k^{th} inequality constraint.

It is quite usual in multi-objective optimization that one objective improved leads to deterioration of the other, therefore it is not possible to have a single solution that fulfils all the objective functions. The best solution that could be used instead for multi-objective optimization simulations is Pareto optimal solutions. From the Pareto optimal Front, it is needed to find the best solution that could be used instead, which includes all the objective functions **(Suganthi, et al., 216)**.

According to **(Caramia &Dell'olmo, 2088)**, A single-objective optimization problem from its basis can be represented as follows:

$$min\ f\ (x) \tag{2.37}$$

$$x\ \in\ S, \tag{2.38}$$

where f is a scalar function and S is the (implicit) set of constraints that can be defined as follow:

$$S\ =\ \{x\ \in\ Rm :\ h(x)\ =\ 0, g(x)\ \geq\ 0\}. \tag{2.39}$$

Therefore the multi-objective optimization expression is mathematically described as follows:

$$min[\, f1(x), f2(x), \ldots, fn(x)] \tag{2.40}$$

$$x \in S, \quad (2.41)$$

where $n > 1$ and S is the constraints set defined above. The objective space is the property at which the objective vector occupies, and the attained set is the image of the feasible set under F. The set is expressed as follows:

$$C = \{y \in Rn : y = f\ (x), x \in S\}. \quad (2.42)$$

The concept of scalar of optimality does not directly apply in the multi-objective setting, instead the notion of Pareto optimality is introduced. Essentially, a vector $x * \in S$ is said to be Pareto optimal for a multi-objective problem if all other vectors $x \in S$ have a higher value for at least one of the objective functions f_i, with $i = 1, \ldots, n$, or have the same value for all the objective functions**(Caramia &Dell'olmo, 2088)**. Following are Pareto optimality definitions according to **(Marler & Arora, 2004).**

Pareto Optimality definitions

Definition 1. Pareto Optimal: A point, $x * \in X$, is Pareto optimal iff,no another point exists, $x \in X$, such that $F(x) \leq F(x *), and\ Fi\ (x) < Fi\ (x *)$ for at least one function. According to **(Athan & Papalambros 1996), (Chen et al. 2000)**, all Pareto optimal points lie on the boundary of the feasible criterion space Z. In most cases algorithms give solutions that may not be Pareto optimal but able to satisfy other criteria and making them important for practical applications. For instance, the following definition defines weakly Pareto optimal.

Definition 2. Weakly Pareto Optimal: A point, $x * \in X$, is weakly Pareto optimal iff there does not exist another point, $x \in X$, such that $F(x) < F(x *)$.

A point is weakly Pareto optimal if there is no other point that improves all of the objective functions simultaneously. In contrast, a point is Pareto optimal if there is no other point that improves at least one objective function without weakening the other function **(Marler & Arora, 2004)**. Therefore Pareto optimal points are weakly Pareto optimal, but weakly Pareto optimal points are not Pareto optimal. All Pareto optimal points may be categorized as being either proper or improper. The idea of proper Pareto optimality and its relevance to certain algorithms is defined bellow.

Definition 3. Properly Pareto Optimal: A point, $x * \in X$, is properly Pareto optimal (in the sense of Geoffrion) if it is Pareto optimal and there is some real number $M > 0$ such that for each $Fi\ (x)$ and each $x \in X$ satisfying $Fi\ (x) < Fi\ (x *)$, there exists at least one $Fj\ (x)$ such that $Fj\ (x *) < Fj\ (x)$ and $\frac{Fi(x*)-Fi(x)}{Fj\ (x)-Fj\ (x*)} \leq M$. If a Pareto optimal point is not proper, it is improper. The quotient is referred to as a trade-off , and it represents the increment in objective function j resulting from a decrement in objective function i. Definition 3 requires that the trade-off between each function and at least one other function be bounded in order for a point to be properly Pareto optimal **(Marler & Arora, 2004)**.

2.6. DIFFERENTIAL EVOLUTION ALGORITHM

Introduced in 1995 by Storn and Prince, Differential Evolution (DE) has already dominated the evolutionary optimization research for computing and engineering field due to its advantageous characteristics. DE is an Evolutionary Optimization method that is easy to use, simple to implement yet efficient in solving optimization problem, it is fast and reliable to converge to true optimum. DE is one of the Evolutionary Algorithms (EA) and it is classified as a population–based, derivative free metaheuristic optimization algorithm that mimics Charles Darwinian evolution and evolves a population of individuals from one generation to another by corresponding evolutionary operations such as mutation, crossover and selection**(Ganbavale, 2014).**

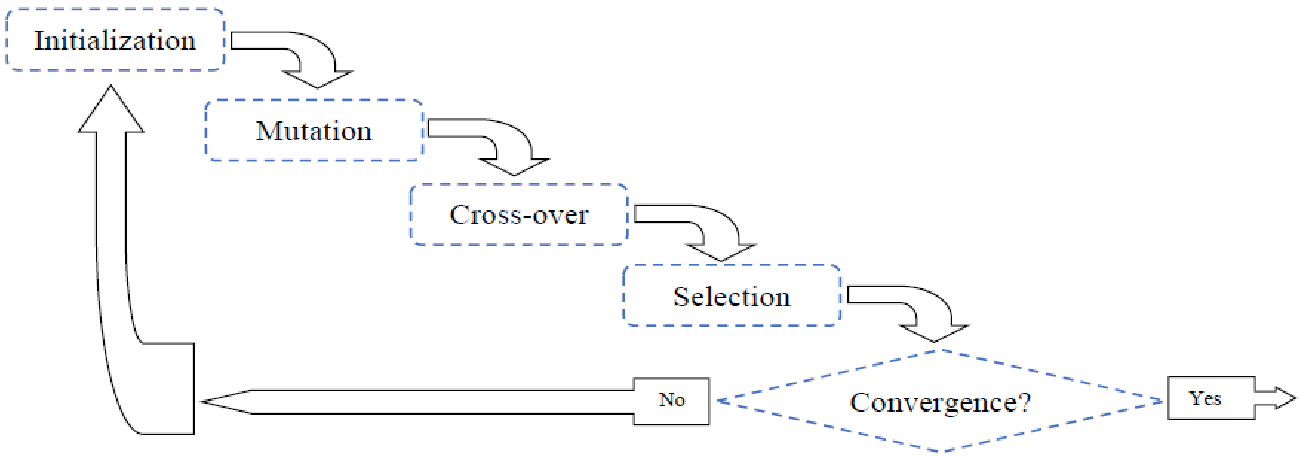


Figure 2.21: Steps involves differential evolution algorithm(Ganbavale, 2014).

DE is a derivative-free continuous optimizer of objective function in nature, it converts parameters as numbers of floating-points and handles them with simple addition, subtraction, and multiplication arithmetic operations and creates new points that are the mutations of existing points. Therefore a parent vector mutated by DE in the population with a scaled difference of other randomly selected individual vectors**(Ganbavale, 2014)**. The resultant mutation vector and the corresponding parent vector are crossed over to create a trial or offspring vector. During the one-by-one selection process of each set of offspring and parent vectors, the one with a better fitness value survives and enters the next generation. The process is repeated for each parent vector and all parent-offspring pair survivors become the parents of a new generation in the evolutionary search cycle. The evolutionary search stops when the algorithm converges to the true optimum solution or when a certain termination criterion such as the number of iterations is reached**(Ganbavale, 2014)**. Following are analogous evolutionary operations taken during optimization of objective function by DE.

2.6.1. Population Structure

Differential Evolution's most implementation capability retains a set of vector populations which contain N_p D-dimensional vectors of real-valued parameters(**Price, et al., 2005)**. Vectors, $X_{i,g}$ that have previously been discovered to be acceptable either as starting points, or by comparing them with other vectors, make the current population, represented by P_X:

$$P_{X,g,} = (X_{i,}), \qquad i = 0,1,\ldots,N_p - 1, \qquad g = 0,1,\ldots g_{max'} \tag{2.43}$$

$$X_{i,,} = (x_{j,i,g}), \quad j = 0,1,\ldots,D - 1, \tag{2.44}$$

Indices start with 0 to make ease dealing with modular arithmetic and arrays. The generation to which a vector belongs is denoted by index, $g = 0,1,\ldots g_{max}$,. A Population index, i, which operates from 0 to $N_p - 1$ is allocated for each vector. Parameters within vectors are indexed with j, which operates from 0 to D – 1. Once initialized, DE mutates vectors that are randomly chosen to create an intermediate agent population, $P_{v,,,}$ of Np mutant vectors, $V_{i,g}$:

$$P_{V,g,} = (V_{i,}), \qquad i = 0,1,\ldots,N_p - 1, \qquad g = 0,1,\ldots g_{max'} \tag{2.45}$$

$$V_{i,} = (v_{j,i,g}), \quad j = 0,1,\ldots,D - 1, \tag{2.46}$$

In the current population, each vector is then reunited with a mutant vector to create a trial population, $P_{\mathbf{u}}$, of N_p trial vectors, $\mathbf{u}_{i,}$:

$$P_{u,g,} = (\mathbf{u}_{i,}), \qquad i = 0,1,\ldots,N_p - 1, \qquad g = 0,1,\ldots g_{max'} \tag{2.47}$$

$$\mathbf{u}_{i,} = (u_{j,i,g}), \qquad j = 0,1,\ldots,D - 1, \tag{2.48}$$

Trial vectors overwrite the mutant population during recombination so that a single array can hold both populations(**Price, et al., 2005)**.

2.6.2. Initialization

Before initiation of population, for each parameter both upper and lower bounds must be specified. The values of 2*D* can be collected into two, *D*-dimensional initiation vectors, **b**L and **b**U, for which subscripts L and U symbolises the lower and upper bounds, respectively. After initialization bounds have been specified, a random generator of number allocates each parameter of every vector a value from within the prescribed range(**Price, et al., 2005)**.. For example, the initial value (g = 0) of the jth parameter of the ith vector is

$$x_{j,,0} = \text{rand}_j(0,1) \,.\, (b_{j,U} - b_{j,L}) + b_{j,L} \,. \tag{2.49}$$

The random number generator, $\text{rand}_j(0,1)$, reverts a random number that is uniformly distributed from within the range [0,1), i.e., $0 \le \text{rand}_j(0,1) < 1$, the subscript, j, gives an indication of a new generated random value for each parameter. The variable is initialized with a real value regardless whether it is integral or discrete since DE considers all variables as floating-point values internally regardless of their type.

2.6.3. Mutation

After DE is initialized, it recombines and mutates the population to produce a population of N_p trial vectors. A randomly sampled, scaled vector difference is added by differential mutation to a third vector(**Price, et al., 2005)**. Equations 2.50, 2.51 and 2.52 shows how to combine three different, randomly chosen vectors to create a mutant vector, $v_{i,}$:

DE/rand/1 $\quad v_{i,g} = X_{r0,} + F_i\,(X_{r1,} - X_{r2,})$ (2.50)

DE/ current-to-rest/1 $\quad v_{i,g} = X_{i,} + F_i\,(X_{best,} - X_{i,}) + F_i\,(X_{r1,} - X_{r2,})$ (2.51)

DE/best/1 $\quad v_{i,g} = X_{best,} + F_i\,(X_{r1,} - X_{r2,})$ (2.52)

The mutation factor, $F \in (0,1+)$, is a positive real number that controls the population evolution rate. While there is no upper limit on *F*, effective values are occasionally greater than 1.0. The *base vector* index, *r*0, can be determined in a number of different ways, but for now it is pretended to be a vector index that is randomly chosen that is different from the *target vector* index, *i*. Except for being different from each other and from both the target and base vector indices, the *difference vector* indices, *r*1 and *r*2, are also randomly selected once per mutant(**Price, et al., 2005)**.

2.6.4. Crossover

Sometimes referred to as discrete recombination, uniform crossover is employed by DE to complement the differential mutation search strategy. Crossover creates trial vectors out of parameter values that have been copied from two different vectors. DE crosses each vector with a mutant vector:

$$u_{i,g} = (u_{1,i,g}, u_{2,i,g}, \dots\ ., u_{D,i,g}) \tag{2.53}$$

$$u_{j,,} = \begin{cases} vj,i,g\ \dots\ \dots\ if\ randj(0,1)\ \leq\ Cri\ or\ j\ =\ jrand \\ xj,i,g\ \dots\ \dots\ \dots\ otherwise \end{cases} \tag{2.54}$$

The crossover probability, $Cr \in [0,1]$, is a user-defined value that controls the parameter values fraction that are copied from the mutant. Uniform crossover compares Cr to the output of a uniform random number generator, $rand_j(0,1)$ to determine which source contributes a given parameter. If the random number is less than or equal to Cr, the trial parameter is inherited from the mutant, $v_{i,}$; otherwise, the parameter is copied from the vector, $x_{i,g}$. Furthermore, the trial parameter with randomly chosen index, j_{rand}, is taken from the mutant to ensure that the trial vector does not duplicate $x_{i,}$. Cr only approximates the true probability pCr, because of this additional demand, that a trial parameter will be received from the mutant(**Price, et al., 2005)**.

2.6.5. Selection

If the trial vector, $u_{i,}$ has an equal or lower objective value than that of its target vector, $x_{i,}$ it replaces the target vector in the next generation; otherwise, the target keeps its place in the population for at least one more generation (Eq. 2.55). By comparing each trial vector with the target vector from which it inherits parameters, DE more tightly integrates recombination and selection than do other EAs:

$$X_{i,+1} = \begin{cases} ui, g \; \ldots \ldots \; if \; f(ui, g) \; < \; Xi, g \\ Xi, g \; \ldots \ldots \ldots \ldots \ldots \; otherwise \end{cases} \tag{2.55}$$

Once the new population is installed, the process of mutation, recombination and selection is repeated until the optimum is located, or a pre-specified termination criterion is satisfied, e.g., the number of iterations reaches a pre-set maximum, $g_{\max}$ (**Price, et al., 2005)**.

2.7. Conclusion

This chapter has presented the overview, definition and challenges encountered in smart grid. It has also outlined different methods used to better smart grids mission such has integration of wind and solar energy for economical purpose. The chapter further outlined previously done studies of differential evolution, DVR and power quality. It also highlighted sections that are key to archive Differential Evolution improvement and optimization of power quality in smart grid. The following chapter will apply theories and contribution studies to archive improved Differential Evolution.

CHAPTER 3

IMPROVED DIFFERENTIAL EVOLUTION BASED ON MUTATION STRATEGIES

This chapter attempts to improve Differential Evolution Algorithm by modifying DE's mutation strategies. On the process, the chapter gives overview of classical Differential Evolution and it outlines modified strategies of DE. The chapter further outlines the methodology and steps taken during simulations to validate the proposed study. In this chapter the analysis of the results are made and the conclusion is made based on the experiment conducted.

3.1. Differential Evolution overview

Much attention from various researchers and research institutions has been received by Differential Evolution (DE) since its introduction by Storn and Price twenty years ago. DE's acknowledgement involves its simplicity, speed, robustness and reliability to converge to true optimum when optimizing an objective function. DE has received much more success in series of benchmark academic competitions, **real world optimization applications** and **black box global optimization competitions**, leading to a big recognition and interest from both researchers and practitioners**(Opara, & Arabas, 2017), (Wu, et al., 2017)**. As discussed in previous chapter, DE employs the basis of population randomly determined sequence search method instead of mathematical operations that are complex **(Zheng, et al., 2017)**. By trait, DE is recognized as a reliable and efficient global optimizer for variety of optimization fields such as multimodal optimization, constrained and unconstrained optimization, and multi-objective optimization **(Wu, et al., 2017)**.

Besides DE algorithm being looked upon as one of the best reliable and efficient EA method for solving problems of optimization, it also has its own drawbacks. DE encounters stagnation, which in-turn disintegrates its performance. Stagnation is a state whereby the process of searching for optimum stops running before finding a global optimal solution. Stagnation is different from premature convergence in a sense that population remains diverse and not converged after the occurrence of stagnation, but the process of optimization does not continue **(Lampinen & Zelinka, 2009)**. When the stagnation occurs, the algorithm is caused not to get better solutions from the candidate solutions that are newly developed, even though the multiform of the population is retained **(Zheng, et al., 2017)**. Chances of stagnation occurrence depend on the availability of number of different potential trial vectors and their survival chances in the following generations **(Zheng, et al., 2017)**.

In this chapter, the improvement of DE is proposed, on the basis of modification of mutation schemes and control parameters tuning. The research looks to improve the convergence speed of DE without encountering stagnation, thereby improving DE reliability on problem optimization. Once DE is improved it will be employed for power quality optimization in smart grid. DE's performance is determined by mutation function, this is due to the fact that new solutions are created from randomly selected individuals from population scaled by mutation factor **(Leon & Xiong, 2014)**, therefore it plays an important role during problem optimization, unlike Genetic Algorithm which is affected by crossover function during optimization process**(Thangaraj, Pant & Abraham, 2010)**. DE's general notation is presented as DE/X/Y/Z, where X denotes the mutation vector, Y denotes the number of difference vectors used and Z denotes the exponential or binomial crossover scheme **(Thangaraj, Pant & Abraham, 2010)**. As reported by **(Opara, & Arabas, 2017)**, Differential mutation contains two parts, selection of base vector and summing of the difference vectors.

3.1.1. Classical Differential Evolution

DE algorithm is one of the based populated stochastic evolutionary algorithm that construct random search and optimization procedures by following Charles Darwin's natural evolutionary principles. The term Differential Evolution is due to a special type of difference vector exists, as explained in **(Chattopadhyay, Sanyal & Chandra, 2011)**. During optimization process, DE retains candidate solutions population and produces new candidate solutions by combining existing candidate solutions according to their simple formulae. The best candidate solution with better fitness on the optimization problem is retained **(Sagoo ,2012).**Unlike other evolutionary algorithms, DE employs selection of only three control parameters, being Mutation Factor (F), Population Size (PS) and Crossover rate (Cr). According to **(Penunuri, et al., 2015),** number of generations (g_{max}) is not recognized as a control parameter, since some stopping criteria is need on the simulation. However, it is very helpful to have an estimation number of generations (g_{max}) in order to avert a very long running time of the program. Mutation factor F value can be selected on the ranges from 0.1 to 2.0 while the Crossover rate value can be selected on the ranges from 0.1 to 1.0. Population size is determined by the Dimensions D of the optimization problem, where the values from 5D to 10D are proposed. However, the values are extended from 2D up to 40D **(Penunuri, et al., 2015).**

As discussed in chapter 2.6, DE uses three evolutionary functions during problem optimization, being mutation function, crossover function and selection function. Mutation function produces variations randomly to existing individuals to furnish new communicated knowledge into the population. The functioning produces mutation vectors at each generation stage, based on the population of the current parent **(Ganbavale, 2014)**. Detailed mutation strategy equations are presented on chapter 2.6, equations (2.50)-(2.52).

The crossover function executes an exchange of communicated knowledge between different individuals in the current population. The final trial vector is created by binomial crossover operation **(Ganbavale, 2014)**. Detailed crossover function equations are presented on chapter 2.6, equations (2.53)-(2.54).

The selection function is a bridge for a driving force towards the most favorable point by preferring individuals of better fitness. The selection operation selects the better individual vector from the parent vector and the trial vector, according to their fitness values **(Ganbavale, 2014)**. Detailed selection function equations are presented on chapter 2.6, equation (2.55).

3.2. DE Improvement

Two factors have been put into consideration for DE improvement, control parameter tuning to obtain the suitable combination to be employed on a selected mutation scheme is first factor. At this instance the mutation scheme selected is DE/rand/1 because of its fast and best convergence. DE/rand/1 is the most frequently used scheme due to its simplicity and best optimum convergence during problem optimization **(Wu, Lee & Chien, 2011)**. Modification of selected mutation scheme is the second factor. The developing of three modified mutation schemes is done by putting responsibility to Mutation Factor F on mutation formula. As reported by **(Tayal & Gupta, 2012),** mutation is the element that separates one DE strategy from the other. Mutation is accountable for expansion and exploration of the search space in order to obtain the optimum solution for a given optimization problem, by combining different parameter vectors in such a manner that a new population vector, termed donor vector is created**(Chattopadhyay, Sanyal & Chandra, 2011)**. Mutation F is accountable for the differential variation amplification **(Chattopadhyay, Sanyal & Chandra, 2011)**-**(Sarker, Elsayed & Ray, 2014)**. In in this modification instance, mutation factor F will also be employed to amplify the base vector $Xr0$ in order to explore much wider search space for better optimum solution. For the first modification, the individual vector $Xr0$ is squired and divided by mutation factor F with reference from chapter 2 equation (2.50), (**Price, et al., 2005),** as shown in the equation (3.1) below. The equation will be named DE/Modi/1,

$$\text{DE/Modi/1} \quad vi, = (Xr0)^2, \div \mathrm{F}i + Fi\,(Xr1, - Xr2,) \tag{3.1}$$

where,

$r0, r1, r2$ = difference integers uniformly chosen from the set $\{1,2, \ldots . . , N\}\backslash\{i\}$,

$Xr1, - Xr2,$= difference vector to mutate the parent,

$Xr0$, = base vector

Fi = mutation factor which the ranges of (0, 1+) interval

On the second modification, the parent vector is multiplied by the mutation factor F. At this instance the individual vector is not squired as shown in the next equation. The equation will be named DE/Modi/2

$$\text{DE/Modi/2} \quad vi, = \text{F}i \times Xr0, + Fi\,(Xr1, - Xr2,) \tag{3.2}$$

The third and final modification involves three factors applied to the individual vector. First, the base vector $Xr0$ is squired as done on the first modification of equation (3.1), secondly, the base vector $Xr0$ is it is multiplied by the mutation factor F , and thirdly, it is divided by 2 as shown in the equation below. The equation will be named DE/Modi/3

$$\text{DE/Modi/3} \quad vi, = \text{F}i \times (Xr0)^2 \div 2 + Fi\,(Xr1, - Xr2,) \tag{3.3}$$

3.3. Methodology

Following are steps that were employed during simulation of the DE improvement by means of mutation scheme modification and tuning of control parameter. The following benchmark functions were used to during simulation of the experiment: Sphere Function, Ackley function, Rastrogin function, Griewank Function, SumPower Function, Schwefel Function, Bukin Function and SumSquare Function. DE/rand/1 is selected for the experiment.

Step 1: Psue-code of DE/rand/1 is done on matlab and the control parameters Settings are done in the following manner: the constant parameters: PS = 50, D = 2, I_max = 200. The varying parameters:, Cr = [0.1 – 1.0], F = [0.1–2.0].

Step 2: Each above-mentioned benchmark function is assessed by varying F and C from 0.1 to 2.0 and from 0.1 to 1.0 respectively so that the perfect set of values that makes a fast convergence on the optimization process is determined.

Step 3: The determined F and C set values are then employed without being varied in three mutation schemes modified. At this instance the determined F/C set Combination values are 0.2/0.2, 0.2/0.3, 0.2/0.5, 0.2/0.7, 0.2/0.9, 0.1/0.9, 0.4/0.9, 0.6/0.9 and 0.8/0.9. All the convergence results of all the mentioned benchmark functions above during F/C combination are tabled and will be used for comparison with the convergence results that are obtained on the mutation schemes modified.

Step 4: The classical mutation scheme DE/rand/1 equaion is modified on the basis of the mutation schemes modifications mentioned above. Following are the control parameters on the mutation schemes modified, PS = 50, D = 2, F = 0.2, 0.1, 0.4, 0.6 and 0.8, C = 0.9, 0.2, 0.3, 0.5, 0.7 and 0.9, I_max = 200.

Step 5: simulations are done in all the benchmark functions for convergence speed for DE/Modi/1, DE/Modi/2 and DE/Modi/3. All results are tabled for comparison with the DE/rand/1 results.

Step 6: Time complexity and statistical data will be determined**.**

Following is Differential Evolution pseudo-code presented with one of the modified mutation scheme DE/Modi/3.

```
Set NP, C, F, parameters
initialize population p= {x1, x2, x3...xm}, x1 ϵ D
repeat
for i=1 to NP do
        Generate MxN matrix
        for m=1:M
          for n=1:N
             X(m,n)=X_min(n)+rand()*(X_max(n)-X_min(n));
          end
        end
    generate a new mutant vector
    y = (xr1)^2*Fx/2+ Fx *(xr2 –Xr3)
                  if f(y) < f(x) then insert y into the new generation
                     else insert x into new generation
                  end
  end
until stopping criteria
```

Figure 3.1: pseudo- code of DE/Modi/3.

3.4. Results

The Following results were obtained during simulation of the eight benchmark functions. The following parameters were employed for all simulations: I_max = 200 iterations, D = 2, PS = 50 and F/C combination = 0.2/0.2, 0.2/0.3, 0.2/0.5, 0.2/0.7, 0.2/0.9, 0.1/0.9, 0.4/0.9, 0.6/0.9 and 0.8/0.9.

Following are the table parameters: F/C is Mutation Factor/ Crossover rate combination used for simulations. Ttot is the total time in seconds (s) taken for a function to complete running during 200 Iterations, it is determined by tic toc psue-code in MATLAB. Fit is the fitness of the optimized function Tc is the time in seconds (s) taken for a function to start convergence during simulation. Tc is determined by the following formula:

$$Tc = (Ttot \times I\_t)/I\_max \quad (3.4)$$

Where Ttot is the total running time of a function,

I_t is the iteration number where the function starts to converge. I_t is determined with reference to Figure 3.2, where X value of 95 is the I_t and the Y value is the minimum best fitness value for a function. Following are the results of DE/rand/1 strategy, DE/Modi/1 strategy, DE/Modi/2 strategy and DE/Modi/3 strategy.

TABLE 3.1A: DE/rand/1 Results

DE/RAND1/Schwefel			DE/RAND1/Sphere			DE/RAND1/Rastrigin			DE/RAND1/Ackley			
fit	Tc	T_{tot}	fit	Tc	T_{tot}	fit	Tc	T_{tot}	fit	Tc	T_{tot}	F /C
8.74e-10	2.73	9.32	3.42e-26	3.4	9.21	0	3.08	9.33	1.87e-10	14.63	41.79	0.2/0.2
8.94e-10	2.97	9.44	5.05e-26	3.41	9.10	0	3.07	9.69	3.63e-10	10.71	32.45	0.2/0.3
6.55e-10	2.97	9.44	5.43e-26	3.41	9.21	0	3.15	9.40	1.07e-10	10.80	32.23	0.2/0.5
6.05e-10	2.87	9.42	1.37e-26	3.47	9.26	0	3.52	9.38	3.21e-10	11.03	33.93	0.2/0.7
5.03e-10	2.90	9.35	8.89e-26	3.25	9.29	0	3.00	9.39	7.98e-10	8.97	33.24	0.2/0.9
9.09e-4	3.18	9.36	0.00046	3.28	9.25	0.0022	3.18	9.63	3.02e-4	17.87	37.23	0.1/0.9
9.0e-10	2.85	9.35	8.26e-26	3.53	9.28	0	3.13	9.34	4.01e-10	10.11	30.62	0.4/0.9
2.45e-11	4.28	9.31	9.84e-27	4.46	9.11	0	5.11	9.38	9.73e-10	11.76	29.39	0.6/0.9
6.17e-10	5.29	9.37	3.13e-26	5.46	9.18	0	5.60	9.41	7.45e-10	15.11	27.73	0.8/0.9

TABLE 3.1B: DE/rand/1 Results

DE/RAND1/SumSquare			DE/RAND1/SumPower			DE/RAND1/Bukin			DE/RAND1/Griewank			
fit	Tc	T_{tot}	fit	Tc	T_{tot}	fit	Tc	T_{tot}	fit	Tc	T_{tot}	F /C
1.94e-23	3.07	9.46	4.05e-27	3.42	10.51	0.1434	8.82	10.26	0.0072	2.54	8.32	0.2/0.2
8.94e-23	3.16	9.28	5.97e-27	4.00	11.10	0.05402	6.46	10.46	0	5.40	8.30	0.2/0.3
7.26e-24	2.80	9.17	3.68e-27	3.77	10.62	0.08762	5.43	10.25	0.00027	5.02	8.30	0.2/0.5
2.84e-23	2.68	9.23	5.60e-27	3.58	10.53	0.1164	3.76	10.31	0	4.12	8.40	0.2/0.7
9.87e-19	2.45	9.23	4.43e-20	2.63	10.74	0.07097	3.71	10.30	0.0074	2.84	8.48	0.2/0.9
1.14e-5	1.98	9.23	0.00014	2.01	10.60	0.07897	4.13	10.19	0.02961	1.68	8.39	0.1/0.9
7.48e-23	2.99	9.20	6.46e-27	3.45	10.62	0.03752	4.31	10.14	0	4.33	8.33	0.4/0.9
3.54e-23	3.64	9.21	6.63e-27	4.18	10.60	0.09985	8.42	10.21	0.00742	5.19	8.30	0.6/0.9
8.69e-23	3.64	9.19	1.86e-27	4.82	10.59	0.06985	9.56	10.22	0.00033	4.2	8.39	0.8/0.9

TABLE 3.2A: DE/Modi/1 Results

DE/ Modi 1/Schwefel			DE/ Modi 1/Sphere			DE/ Modi 1/Rastrigin			DE/ Modi 1/Ackley			
fit	Tc	T_{tot}	fit	Tc	T_{tot}	fit	Tc	T_{tot}	fit	Tc	T_{tot}	F /C
9.54e-11	6.29	9.32	7.00e-26	1.78	9.14	0	1.83	9.63	8.87e-10	17.45	30.35	0.2/0.2
1.03e-10	4.32	9.30	3.92e-26	1.78	10.5	0	1.84	9.41	3.60e-10	20.83	31.56	0.2/0.3
2.994	5.98	9.35	7.14e-26	1.23	9.11	0	1.60	9.41	4.19e-10	13.15	30.59	0.2/0.5
4.895	5.19	9.44	4.93e-27	1.19	9.15	0	1.83	9.38	1.84e-10	11.51	30.69	0.2/0.7
6.89e-10	7.64	9.32	9.95e-27	1.18	9.10	0	2.15	9.36	9.92e-11	10.82	27.75	0.2/0.9
1.375	8.22	9.34	1.59e-27	0.91	10.68	0	1.38	9.54	4.99	22.03	31.25	0.1/0.9
5.83e-10	6.30	9.40	4.08e-26	1.65	9.17	0	2.86	9.22	8.594	28.50	31.15	0.4/0.9
5.88e-10	6.32	9.36	3.45e-26	2.20	9.16	0	3.22	9.34	7.17e-10	22.84	30.45	0.6/0.9
1.84e-07	9.1	9.38	8.62e-26	3.54	9.20	0	4.8	9.33	8.34e-10	26.57	29.36	0.8/0.9

TABLE 3.2B: DE/Modi/1 Results

DE/ Modi1/SumSquare			DE/Modi1/SumPower			DE/ Modi1/Bukin			DE/Modi1/Griewank			
fit	Tc	T_{tot}	fit	Tc	T_{tot}	fit	Tc	T_{tot}	fit	Tc	T_{tot}	F /C
2.73e-22	1.39	9.24	6.92e-27	2.83	10.88	7.267	1.43	10.19	0.03725	3.46	8.43	0.2/0.2
5.05e-23	1.44	9.26	1.22e-28	2.39	10.64	2.682	4.08	10.19	1.72e-05	8.17	8.51	0.2/0.3
8.17e-23	1.15	9.23	2.458e-27	3.50	10.60	3.939	1.66	10.35	0.07941	6.77	8.25	0.2/0.5
9.68e-23	1.05	9.51	1.17e-27	2.64	10.57	9.426	1.30	10.31	0.2251	1.70	8.31	0.2/0.7
9.87e-23	1.61	9.22	1.87e-28	2.22	10.57	2.808	6.46	10.26	0.0377	5.40	8.25	0.2/0.9
3.14e24	1.33	9.21	5.73e-28	2.12	10.61	1.495	4.92	10.38	0.0329	7.72	8.30	0.1/0.9
4.920e-23	1.43	9.23	4.43e-27	2.80	10.58	4.476	1.22	10.13	0.1983	0.71	8.34	0.4/0.9
6.23e-23	2.02	9.20	7.92e-31	2.70	10.59	3.093	1.08	10.30	0.1993	5.55	8.34	0.6/0.9
1.59e-23	2.49	9.24	5.7e-28	4.83	10.61	1.687	1.18	10.23	0.0629	7.70	8.36	0.8/0.9

TABLE 3.3A: DE/Modi/2 Results

F /C	DE/ Modi2/Schwefel			DE/ Modi2/Sphere			DE/ Modi2/Rastrigin			DE/ Modi3/Ackley		
	fit	Tc	T_{tot}	fit	Tc	T_{tot}	fit	Tc	T_{tot}	fit	Tc	T_{tot}
0.2/0.2	8.16e-11	1.49	9.33	8.79e-26	1.71	9.22	0	1.24	9.91	6.81e-10	4.52	31.14
0.2/0.3	2.07e-10	1.44	9.30	1.89e-26	1.62	9.24	0	1.12	9.30	5.53e-10	4.45	31.76
0.2/0.5	8.85e-10	1.12	9.35	4.54e-27	1.31	9.35	0	1.02	9.31	8.08e-10	3.53	30.68
0.2/0.7	2.18e-10	0.98	9.32	2.68e-26	1.06	9.19	0	0.79	9.33	3.21e-10	3.22	32.19
0.2/0.9	3.38e-10	0.79	9.32	2.02e-26	0.87	9.19	0	0.61	9.34	6.26e-10	2.26	30.19
0.1/0.9	4.76e-10	0.51	9.27	8.54e-28	0.60	9.17	0	0.37	9.33	1.17e-10	1.68	30.53
0.4/0.9	7.76e-10	1.41	9.37	4.49e-26	1.66	9.20	0	1.36	9.39	7.12e-10	4.59	30.59
0.6/0.9	5.49e-10	2.65	9.31	5.68e-26	2.84	9.16	0	2.48	9.34	5.79e-10	9.18	31.12
0.8/0.9	6.54e-11	4.29	9.32	4.74e-26	4.79	9.13	0	4.29	9.32	6.09e-10	16.46	33.60

TABLE 3.3B: DE/Modi/2 Results

F /C	DE/ Modi2/SumSquare			DE/Modi 2/SumPower			DE/ Modi2/Bukin			DE/Modi 2/Griewank		
	fit	Tc	T_{tot}	fit	Tc	T_{tot}	fit	Tc	T_{tot}	fit	Tc	T_{tot}
0.2/0.2	3.06e-23	1.41	9.10	4.06e-28	2.00	10.82	0.1	3.03	10.26	0	1.78	8.47
0.2/0.3	4.47e-23	1.38	9.20	6.25e-28	1.68	10.52	0.1	1.80	10.31	0	1.76	8.28
0.2/0.5	2.97e-23	1.11	9.23	9.00e-27	1.37	10.54	0.1	1.32	10.18	0	1.29	8.34
0.2/0.7	1.96e-24	0.92	9.22	4.55e-27	1.12	10.63	0.1	1.03	10.26	0	1.09	8.37
0.2/0.9	3.13e-23	0.70	9.30	2.39e-28	1.07	10.65	0.1	0.87	10.21	0	0.71	8.83
0.1/0.9	7.24e-24	0.51	9.24	3.23e-28	0.69	10.66	0.1	0.64	10.74	0	0.42	8.33
0.4/0.9	5.47e-23	1.48	9.23	3.66e-27	1.69	10.55	0.1	1.74	10.26	0	1.79	8.33
0.6/0.9	2.55e-23	2.44	9.22	7.90e-27	3.04	10.49	0.1025	4.19	10.22	0	3.73	8.29
0.8/0.9	6.91e-23	4.03	9.27	4.30e-29	5.54	10.45	0.106	7.61	10.29	0	5.11	8.31

TABLE 3.4A: DE/Modi/3 Results

DE/ Modi3/Schwefel			DE/ Modi3/Sphere			DE/ Modi3/Rastrigin			DE/ Modi3/Ackley			
fit	Tc	T_{tot}	fit	Tc	T_{tot}	fit	Tc	T_{tot}	fit	Tc	T_{tot}	F/C
3.96e-10	1.65	9.41	6.97e-27	1.33	9.17	0	1.07	9.33	2.46e-10	4.54	30.25	0.2/0.2
3.86e-10	1.45	9.33	4.22e-26	1.24	9.16	0	1.02	9.31	5.56e-10	4.06	31.24	0.2/0.3
1.45e-10	1.30	9.32	43.08e-27	1.04	9.01	0	0.84	9.31	1.22e-10	3.94	30.29	0.2/0.5
1.18e-10	1.12	9.37	1.25e-25	0.87	9.18	0	0.70	9.29	7.84e-11	2.61	30.71	0.2/0.7
6.13e-11	1.08	9.35	3.05e-26	0.69	9.18	0	0.56	9.34	7.39e-10	2.16	30.87	0.2/0.9
8.20e-10	0.56	9.33	1.57e-26	0.46	9.18	0	0.33	9.41	8.13e-10	1.53	30.62	0.1/0.9
7.63e-10	2.43	9.35	9.36e-26	1.19	9.13	0	1.17	9.32	7.41e-10	4.66	31.06	0.4/0.9
4.60e-10	3.58	9.31	5.53e-26	1.96	9.13	0	1.92	9.14	8.06e-10	9.15	31.01	0.6/0.9
8.51e-10	5.09	9.00	9.21e-26	3.35	9.17	0	4.38	9.43	1.03e-10	12.10	31.44	0.8/0.9

TABLE 3.4B: DE/Modi/3 Results

DE/ Modi3/SumSquare			DE/Modi3/SumPower			DE/ Modi3/Bukin			DE/Modi3/Griewank			
fit	Tc	T_{tot}	fit	Tc	T_{tot}	fit	Tc	T_{tot}	fit	Tc	T_{tot}	F/C
1.52e-22	1.21	9.20	5.51e-28	1.59	10.57	0.1	2.60	10.21	0	2.57	8.28	0.2/0.2
1.40e-23	1.22	9.36	2.93e-28	1.42	10.55	0.1	1.76	10.36	0	2.14	8.23	0.2/0.3
9.53e-23	0.87	9.20	1.32e-28	1.06	10.57	0.1	1.13	10.27	0	2.48	8.41	0.2/0.5
2.54e-23	0.74	9.25	4.31e-28	1.06	10.57	0.1	1.16	10.25	0	1.4	8.22	0.2/0.7
5.46e-23	0.60	9.20	1.54e-27	0.85	10.58	0.1	0.77	10.21	0	1.7	8.26	0.2/0.9
4.15e-25	0.47	9.30	6.36e-28	0.59	10.64	0.1	0.56	10.21	0	0.66	8.23	0.1/0.9
2.14e-23	1.12	9.32	4.62e-27	1.49	10.61	0.1	1.53	10.18	0	4.2	8.31	0.4/0.9
6.81e-27	1.16	9.25	4.69e-27	2.44	10.37	0.1	3.89	10.36	0.014	6.78	8.22	0.6/0.9
8.34e-23	2.91	9.40	8.67e-27	3.92	10.45	0.1	4.81	9.91	0	6.24	7.56	0.8/0.9

From the DE/rand/1 results, table 3.1A and 3.1B, it can be noticed that the convergence of most functions is robust during the parameter combination F/C of 0.2/0.9, with convergence time (Tc) values being the lowest on most functions, except for Schwefel and Griewank function which have their lowest Tc values on F/C of 0.2/0.2 and 0.1/0.9 respectively. It can also be noticed that Griewank function takes too long to converge after the run has been started, with an average Tc value of 4.12 seconds from a total running time (Ttot) of 8.4 seconds, making 51% convergence time.

On DE/Modi/1 results on table 3.2A and 3.2B, it can be noticed that Tc is worse on DE/Modi/1 compared to DE/Rand/1 on Ackley, Schwefel, Griewank and Bukin function. For Rastrigin, Sphere, SumPower and SumSquare function, Tc is better on DE/Modi/1 compared to DE/Rand/1. With Griewank and Bukin function results, minimal optimum is not reached during DE/Modi/1 simulation, making DE/Rand/1 a better mutation scheme compared to DE/Modi/1.

For the Results of DE/Modi/2 on table 3.3A and 3.3B, the mutation scheme has the best results compared to previously discussed schemes above. All Functions research minimal optimum, the convergence time is minimum compared to the previously discussed results. On this mutation strategy the F/C parameter combination of 0.1/0.9 gave the best minimum convergence time with best minimum fitness for all the benchmark functions used on the simulations, making it the best combination that can be used with DE/Modi/2 mutation scheme.

From the results of DE/Modi/3 on table 3.4A and 3.4B, there is a slim deviation of convergence time Tc between DE/Modi/2 and DE/Modi/3. Making F/C combination of 0.1/0.9 the reference due to its minimum convergence time and robust convergence fitness, Tc has improved for all the functions except for Griewank function which slightly dropped improved compared to DE/modi/2.

The statistical data for mutation strategies determines the best, average and worse convergence time Tc of the mutation strategies. In this case the best Tc is ranged between 70%-100%, average Tc being 69%-50% and worse Tc being between 49%-0%. The following formula was used to determine the set points of Tc for every function:

$$Tset = (1 - \%) \times Ttot \tag{3.5}$$

where % is the set percentage for a particular range. Tset is the targeted Tc in seconds (s) for best, average or worse. Ttot being the average total run time in seconds for each function. The set points for Tc best, Tc worse and Tc average were determined and the number of best, average and worse Tc was determined for every mutation strategy. Following is the table that analyses number of best, average and worse Tc for each mutation strategy.

TABLE 3.5: Statistical Data for Mutation strategies

Mutation Strategies	Best	Average	Worse
DE/RAND/1	7	45	20
DE/Modi1	30	6	32
DE/Modi2	61	6	5
DE/Modi3	59	10	3

On the statistical data table above, it can be observed that DE/rand/1 has large number of average convergence time and DE/modi/1 has a worse convergence time, compared to the rest of the strategies, making it the slowest strategy in terms of fast convergence. DE/modi/2 and DE/modi/3 have the best convergence time compare to the other two strategies, making them the fasted strategies with regards to convergence.

Schwefel function was selected to determine the time complexity for each mutation strategy Tc form F/C combination 0f 0.4/0.9, 0.2/0.9 and 0.1/0.9. The following formula was used to calculate the Complexity:

$$C = (T_{0.4/0.9} - T_{0.2/0.9}) / T_{0.1/0.9} \tag{3.6}$$

TABLE 3.6: Time complexity

Mutation Strategies	T0.4/0.9	T0.2/0.9	T0.1/0.9	c
DE/RAND/1	2.99	2.45	1.98	0.27
DE/Modi1	1.43	1.61	1.33	0.14
DE/Modi2	1.48	0.7	0.51	1.53
DE/Modi3	1.12	0.6	0.47	1.11

On table 3.6 it can be noted that the largest complexity is assigned to DE/Modi/2 and DE/Modi/3.

Following figures show the simulated fitness value of the functions obtained during research.

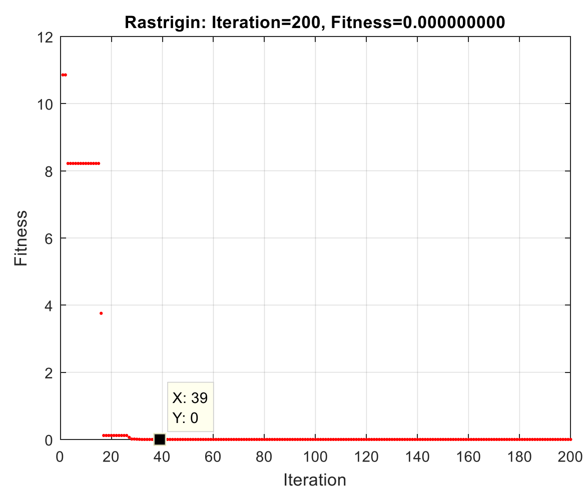


Figure 3.2: Rastrigin's fitness vs iterations.

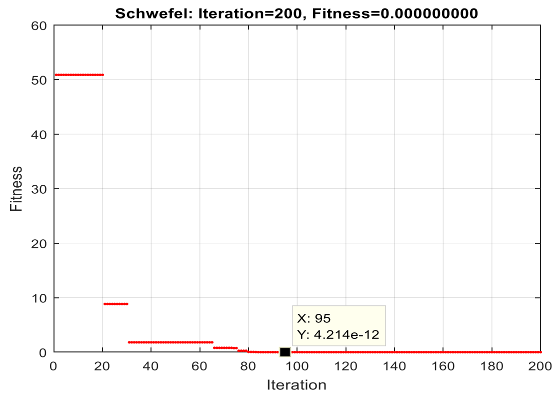


Figure 3.3: Schwefel's fitness vs iterations.

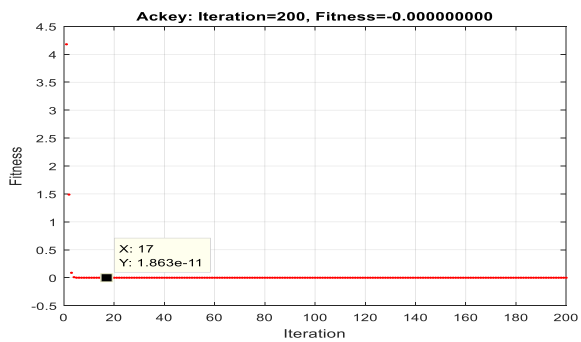


Figure 3.4: Ackley's fitness vs iterations.

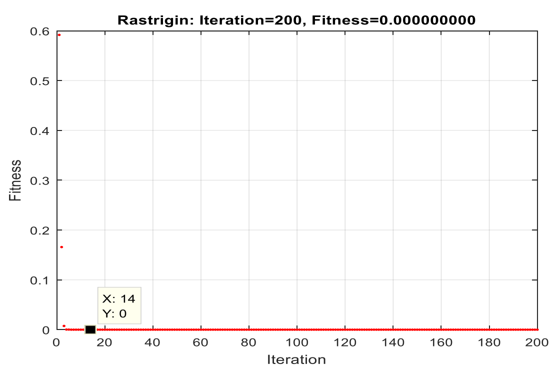


Figure 3.5: Rastrigin's fitness vs iterations.

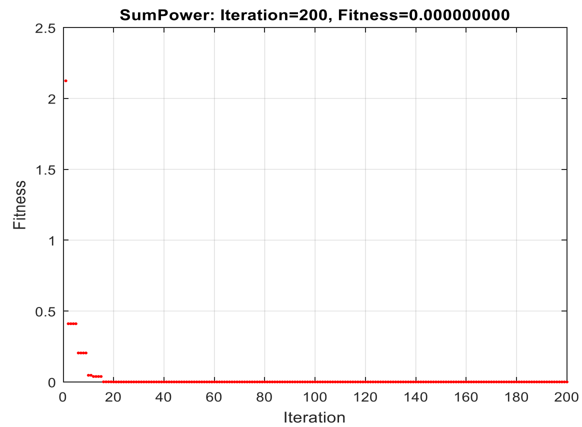


Figure 3.6: Sum-Power's fitness vs iterations.

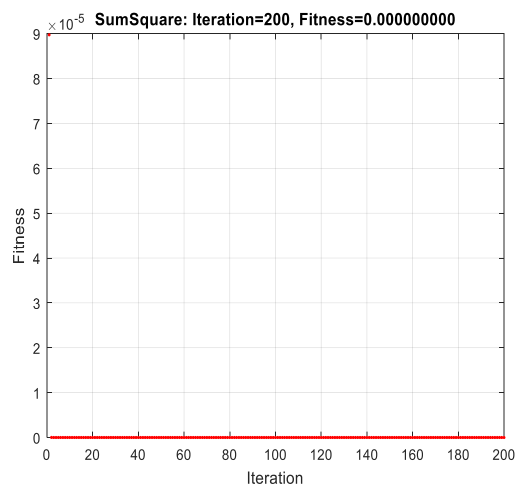


Figure 3.7: Sum-Square's fitness vs iterations.

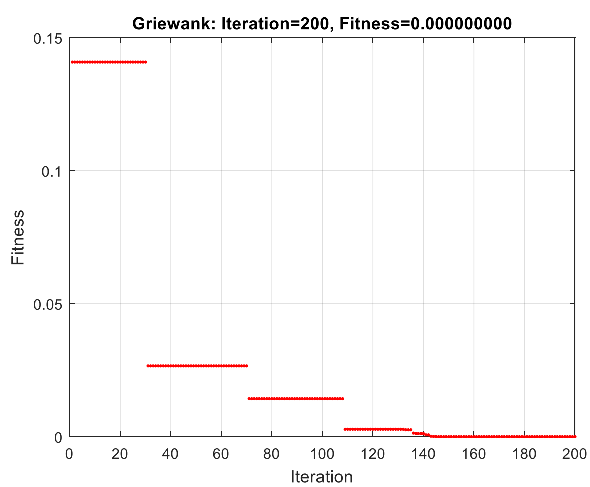


Figure 3.8: Griewank's fitness vs iterations.

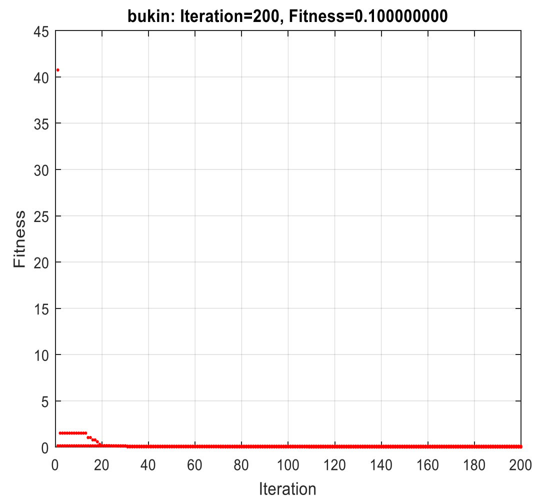


Figure 3.9: Bukin's fitness vs iterations.

3.5. Conclusion

From the basis of the results above, it is observed that the results of DE/Modi/1 are deficient of convergence speed and robustness, achieving only 41.67% of time of best convergence. For DE/Modi/3, the best convergence time is 81.94%, showing improvement compared to classical DE/Rand/1. The best convergence speed and strong convergence results are achieved on DE/Modi/2 with 84.72% of the best time of convergence compared to the rest of the modified strategies. Otherwise 0.1/0.9 F/C combination provided the convergence that is rapid and strong during DE/Modi2 and DE/Modi3 simulation session, becoming best Mutation Factor/ Crossover Rate combination for the DE/Modi2 and DE/Modi3 mutation strategies. Conclusion can be drawn that DE convergence speed improvement has been achieved through modified Mutation strategies DE/Modi2 and DE/Modi/3 with 0.1/0.9 F/C combination. DE/Modi2 and DE/Modi/3 modified mutation strategies with F/C combination of 0.1/0.9 can be employed in future due to their fast and effective convergence speed, robust convergence and ability to optimize Griewank and Bukin function which classical DE/rand/1 was not able to optimize to minimum optimal point.

CHAPTER 4

DYNAMIC VOLTAGE RESTORER BASED POWER QUALITY OPTIMIZATION USING IMPROVED DIFFERENTIAL EVOLUTION ALGORITHM.

This chapter proses the optimization of power quality by employing Dynamic Voltage restorer and improved differential evolution while minimizing two objective functions. The gives overview of smart grid and power quality, it further outlines mathematical modelling of DVR compensator and improved DE. I this chapter the experiment is conducted and it is verified by simulations and the conclusion is made based on the findings of analysis of the results obtained during simulations.

4.1. Smart Grid overview

The rapid growth and development of smart home technologies and production systems technologies in the industries, has led researchers to take a great consideration towards the quality of the power needed to supply those new smart technological developments. However, smart technological developments need a quality power supply that is smart, sustainable, economical, reliable, efficient and pollution free to the environment. Smart grid is the best innovative idea to those requirements. Smart Grid is a modernized automated power grid that is set to overcome the challenges that have previously been experienced by a classical power grid. The challenges that have been experienced by the classical power grid are air pollution to the environment due to fossil fuels, black outages, poor power quality to sensitive electric appliances and equipment, un-economical, unreliable and un-efficient power supply to the society and industrial businesses. Smart grid is set to consider employing a large number of distributed energy sources, renewable energy sources and demand response program coupled energy storage devices**(Melhem, et al., 2018)**. Therefore the existing distribution systems would be intensified**(Casolino, et al., 2017).** However this chapter looks at one of the challenges that the classical power grid experiences, namely power quality.

4.2. Power Quality overview

Power quality has been the subject of many researchers, due to the effects it causes on the daily life of society and industries. Electrical disturbances such as power interruptions, transients, harmonics, swells and sags are the major contributors towards the poor power quality in smart grid**(Hojabri, & Toudeshki, 2013)**. However, Voltage sags and swells are the most contributing electrical disturbances of poor power quality compared to all other mentioned power disturbances due to their frequent occurrence in the power systems**(Thakur & Singh, 2017).** Voltage sag is a reduction of the operational voltage level between 10 to 90% of the root mean square voltage, for the duration of 0.5 cycle to 1 min, while Voltage swell is the increase of the root mean square voltage level from 110% to 180% above the operational voltage level with duration of more than 3 cycles**(Thakur & Singh,**

2017). Voltage sags are sometimes caused by power suppler during the period of heavy demand. Another cause of voltage sags mostly experienced in industries is during the period where heavy plant pulls down the supply voltage during the start-up of heavy load such as Compressors and pumps, which require a high start-up current and switch in and out on a frequent basis**(Edomah, 2009)**. Voltage Swells are caused by switching-on heavy or reactive equipment such as motors, transformers, motor drives or power factor correction equipment**(Edomah, 2009)**. These mentioned power disturbances result in fluctuations of production rates, incorrect operation of equipment, lighting systems dimming, drop out of relays and contactors, damage of electronic equipment and unreliable data in equipment test**(Edomah, 2009)**.

This research looks to improve power quality by considering the Dynamic Voltage Restorer method to compensate voltage swells and voltage sags, based on improved Differential Evolution Algorithm, with two objective functions, one, to minimize voltage swells and two, to minimize voltage sags in the smart grid. In this case Reliability of smart grid also depends on power quality, therefore making power quality one of the important and responsible aspects in smart grid's vision **(Agarwal & Tsoukalas, 2011)**. A Restorer (DVR) has been frequently used for compensation of voltage sags and swells due to its ability to be controlled, high efficiency and its fast response **(Messiha, et al., 2017)**.

Since in this research the focus is to minimize both voltage sag and voltage swell, therefore a multi-objective Differential Evolution algorithm will be used, as they are extensively used to solve such conflicting objectives. Due to the conflicting nature of the objective functions, a number of optimal solutions known as Pareto Front will always get resulted for a multi-objective problem **(Suganthi, et al., 216)**. With Differential Evolution Algorithm (DE) being one of the robust and effective Evolutionary Algorithm, smart grid optimization will look to employee improved DE in order to fulfil power quality that is efficient and reliable to the society and industries.

4.3. Proposed multi-objective power quality optimization based on improved differential evolution

For poor power quality to be overcome in smart grid, two objective functions must be minimized, being voltage sags and voltage swell. For implementing of the fast and effective multi-objective power quality optimizer based on DE, the below circuits are used to demonstrate the robust and effective method to overcome poor power quality in smart grid. Figure 4.1 shows a power system that is assisted by DVR. The system consists of the power supply, supplying sensitive RL load, masked control circuit, battery powered inverter connected to the injecting transformer for voltage compensation during fault. The other parts of the circuit are connected in such a way that voltage sag and voltage swells are created to the system for experiment purpose. Figure 4.2 shows the control circuit of the DVR system. The purpose of the control circuit is to sense a type of fault from the power system circuit and be able to send a signal to the inverter. The inverter mosfets will be turned on to allow the inverter to give power to the transformer to inject the required voltage level for compensation. It is represented by Figure 4.5 and it is a voltage compensation system. The control system uses Phase Locked Loop (PLL) system to sense fault and to synchronize the load voltage level. It can also be noticed that the injected voltage by transformer passes through the series capacitor where the voltage is filtered for harmonics before it is supplied to the load. Figure 4.3 and Figure 4.4 represent the Voltage swell fault generator and voltage sag fault generator respectively. During normal operation of the system, the voltage across to the sensitive RL load is expressed in equation (4.1) below.

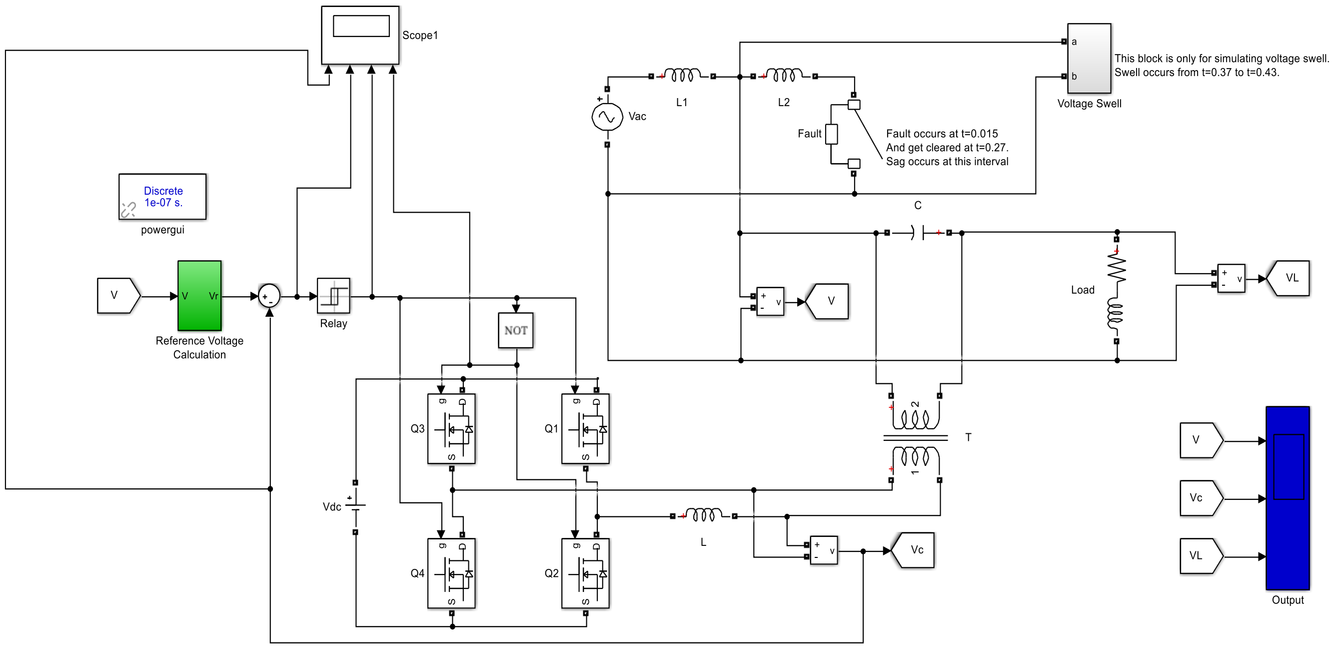


Figure 4.1: DVR system for Sag and swell Compensation.

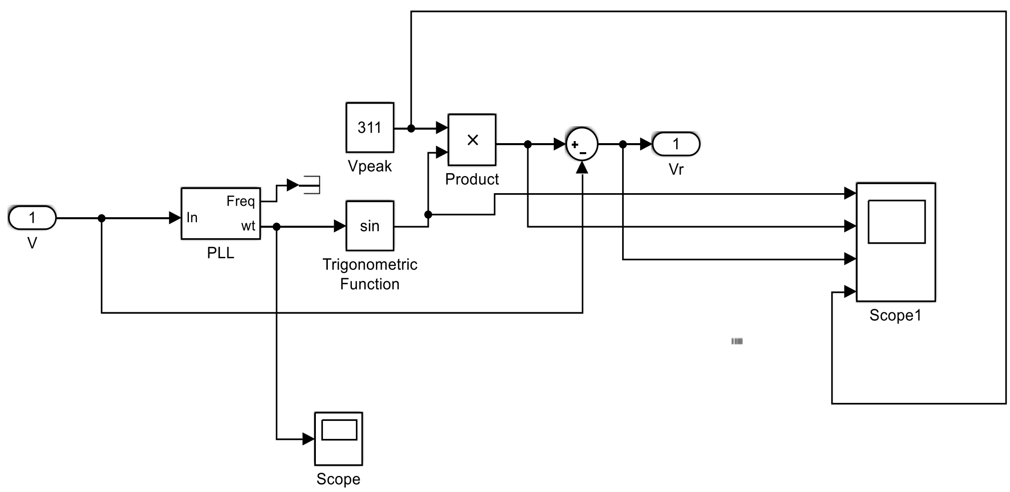


Figure4.2: Control Circuit for DVR

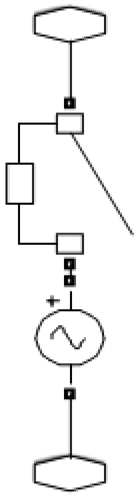


Figure 4.3: Voltage swell fault generator

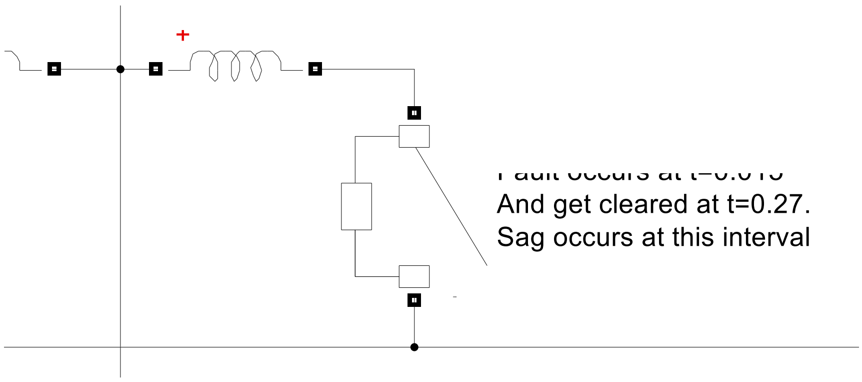


Figure 4.4: Voltage sag fault generator

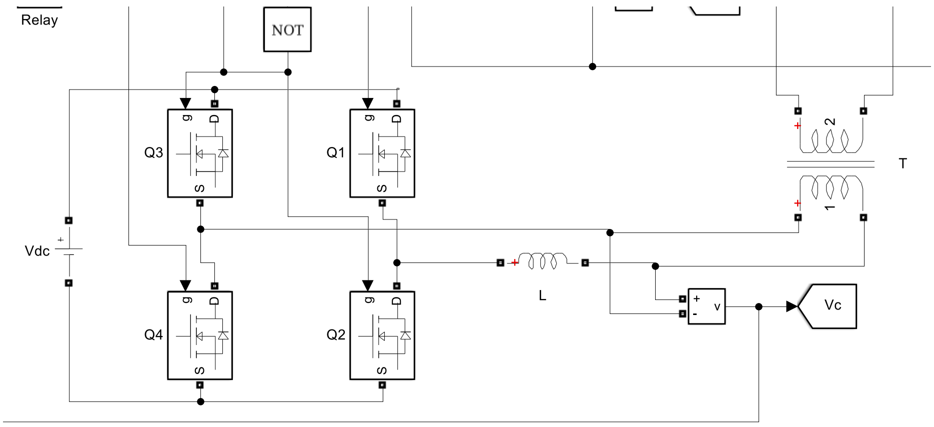


Figure 4.5: Voltage Compensator system

$$V_{RL} = V_{SP} \times \sin(2 \times \pi \times f \times t) \tag{4.1}$$

where,

V_L = sensitive RL load voltage in volts (V),

V_{SP} = the supply voltage from the AC source in volts (V),

f = the ac voltage supply frequency in hertz (Hz)

t = time in seconds (s).

At this stage there is no heavy load switched on that could disturb the normal operation of the sensitive RL load on the system. During when the heavy load is switched on to the system, the voltage sags are caused, reducing the operational voltage level of the sensitive RL load momentarily. Following is the expression during abnormal operation of the system caused by voltage sags due to switching on of the heavy load.

$$V_{LSAG} = \{V_{RL} - V_F \times [H(t\text{-}t_1) - H(t\text{-}t_2)]\} \times \sin(2 \times \pi \times f \times t) \tag{4.2}$$

where,

V_{LSAG} = sensitive RL load voltage during voltage sag disturbance in volts (V),

V_F = the reduction or increment voltage level in volts (V) due to disturbance'

H = Heaviside step response,

t_1 = time when the sag disturbance starts in seconds (s),

t_2 = time when the sag disturbance ends in seconds (s).

V_F is the amount of voltage that is subtracted from normal voltage level during the reduction of the operational voltage level or added to the normal voltage level that results in the increase of normal voltage level above the operational voltage level due to voltage sags and swells respectively. In the case of voltage sags, V_F is subtracted for a period of (t_1 – $t_{2)}$, resulting to a system disturbance for that period. In the case of voltage swells disturbance, V_F is added for a period of (t1 – t2), as expressed in the following equation **(Saveca & Wang & Sun, 2019)**,

$$V_{LSWELL} = \{V_{RL} + V_F \times [H(t\text{-}t_3) - H(t\text{-}t_4)]\} \times \sin(2 \times \pi \times f \times t) \tag{4.3}$$

where,

V_{LSWELL} = sensitive RL load voltage during voltage swell disturbance in volts (V),

t_1 = time when the swell disturbance starts in seconds (s),

t_2 = time when the swell disturbance ends in seconds (s).

Following are equations for DVR's action during the voltage compensation for voltage sags and voltage operational level correction during the voltage swells respectively. For voltage sag compensation, there must be a zero disturbance. Therefore during voltage sags disturbance where V_F creates that disturbance in the system, to compensate and be on zero disturbances, equal value of voltage that is same as of V_F is needed on the system but in opposite polarity of the one of V_F. Therefore,

$$0 = V_F - V_C \qquad (4.4)$$

$$V_F = -V_C \qquad (4.5)$$

$$V_{COMP} = \{-V_C \times [H(t-t_1) - H(t-t_2)]\} \times \sin(2 \times \pi \times f \times t) \qquad (4.6)$$

where,

V_C = the added voltage for compensation or counterbalancing of operational voltage level during DVR action.

V_{COMP} = DVR voltage compensation for voltage sags

Therefore V_C is variable during DVR action in order to certify the objective requirements. The load voltage after compensation becomes as follows,

$$V_L = V_{LSAG} - V_{COMP} \qquad (4.7)$$

For voltage swell correction on the system, the similar action as of voltage sag compensation is performed by DVR for operational voltage level correction during voltage swell disturbance with reference to equation (4.4). In this case the action happens in opposite polarity from the voltage sag compensation.

$$-V_F = V_C \qquad (4.8)$$

$$V_{CORR} = \{V_C \times [H(t-t_3) - H(t-t_4)]\} \times \sin(2 \times \pi \times f \times t) \qquad (4.9)$$

where,

V_{CORR} = DVR operational voltage level correction for voltage swells.

Therefore the load voltage after correction becomes as follows.

$$V_L = V_{LSWELL} - V_{CORR} \qquad (4.10)$$

For voltage sag and swell optimization based on DE, the equations becomes as follows,

$$V_{SAGmin} = V_L - V_{LSAG} \qquad (4.11)$$

$$J_1 = V_{SAGmin} + V_{COMP} \qquad (4.12)$$

$$V_{SWELLmin} = V_L - V_{LSAG} \qquad (4.13)$$

$$J_2 = V_{SWELLmin} + V_{CORR} \tag{4.14}$$

where

V_{SAGmin} = voltage sag occurrence

$V_{SWELLmin}$ = voltage swell occurrence

J_1 = First objective function

J_2 = Second objective function

J_1 and J_2 are multi-objectives to be minimized in smart grid based on proposed Differential Evolution, with V_C being the variable to be controlled during voltage sag compensation and voltage swell counterbalancing.

For optimization of abovementioned objective functions J_1 and J_2, a multi-objective Differential Evolution based on parallel operation strategy will be used. The advantage of the parallel operation multi-objective optimization is that, two more objective functions don't conflict with each other during optimization due to the fact that, the objective functions run parallel once they reach mutation function up until selection, therefore creating a room for one objective function to be optimized effectively to the maximum or to the minimum set target. During operation, the objective functions are initialized with the same control parameters and same limitations. Before mutation operation is introduced, the functions are parallelized, therefore interring the mutation operation in parallel. The functions run parallel until they reach selection operation, therefore resulting in a separate Pareto set graphic presentation. Multi-objective optimization is discussed in **chapter 2.5** and formulas for mutation, crossover and selection functions where the multi-objective functions will go through during optimization respectively are discussed from **chapter 2.6.3 to 2.5.5.**

The proposed DE will be used to optimize the above-mentioned multi-objectives based on developed mutation strategies. DE/Modi/2 and DE/Modi/3 are the mutation strategies to be used and to be compared with DE/Rand/1 mutation strategy because it is the most commonly used strategy due to its simplicity and best convergence during optimization of the problem **(Wu, Lee & Chien, 2011)** and they are discussed in details in **chapter 4.2**. DE/Modi/1 will not be used due to poor performance, lack of robustness and convergence speed, after it just made 41.67% of best convergence time during **(Saveca, Wang & Sun, 2018)** simulation

4.4. Methodology

The following steps were taken during simulation of multi-objective functions on power quality optimization in smart grid based on improved DE in order to validate the research. DE/rand/1 is selected for comparison against the improved mutation strategies.

Step 1: The system is modelled as shown on Figure 4.1 and Figure 4.2 in matlab Simulink in order to demonstrate the DVR action practically. First the simulation is run with DVR disconnected from the system in order to see load voltage behavior before DVR. Secondly the DVR is connected to the system and the load voltage is recorded.

Step 2: The system in Figure 4.1 and Figure 4.2 is coded in MATLAB script file in order to simplify the multi-objective optimization. The simulation is run and the load voltage behavior is recorded by means of graphs.

Step 3: The improved DE is introduced to optimize the multi-objective functions J_1 and J_2. The best combination of parameters is used based on **(Saveca & Wang & Sun, 2018)** conclusion. According to **(Saveca & Wang & Sun, 2018)**, the best mutation factor F and Crossover rate combination is 0.1 and 0.9 respectively, due to their robust convergence. The other control parameter settings are as follows, D = 2, PS = 50, I_max = 200, where D is the dimension, PS is population size and I_max is the maximum Iterations.

Step 4: Multi-objective functions J_1 and J_2 are optimized using DE/rand/1, DE/Modi/2 and DE/Modi/3strategies. Each strategy is ran 5 times in order to check the consistence of the strategy. The results are recorded on the tables for comparison of each strategy.

Following is the pseudo- code for DE with one of the modified mutation scheme DE/Modi/3.

```
Set NP, C, F, parameters
initialize population p= {x1, x2, x3...xm}, x1 ∈ D

compute J1 = V_L – V_sag + V_comp
compute J2 = V_L – V_L_swell + V_L_co;

repeat
for i=1 to NP do
       Generate MxN matrix
       for m=1:M
         for n=1:N
            X(m,n)=X_min(n)+rand()*(X_max(n)-X_min(n));
         end
       end
    generate a new mutant vector
    y = (xr1)^2*Fx/2+ Fx *(xr2 –Xr3)
                   if f(y1) < f(x) then insert y1 into the new generation
                      else insert x into new generation
                   if f(y2) < f(x) then insert y2 into the new generation
                      else insert x into new generation

                   end
   end
until stopping criteria
```

Figure 4.6: DE/Modi/3 pseudo- code for multi-objective

4.5. Results and discussion

During results experiment the operation load voltage is specified to be 400 volts during normal operation. Therefore any load voltage under or over the specified amount is deemed a fault and therefore the system should rectify it For experiment purpose, the extra voltage representing voltage swells and the cut out voltage representing voltage sags has been specified as 50 volts extra and 50 volts under respectively. Following are results taken during simulations of multi-objective power quality optimization in smart grid based on the proposed DE. Following are Simulation settings used during simulation.

Hardware specification:

Lenovo G40

Processor` Intel core(TM)i5-4210U CPU @ 1.70GHz 2.40GHz

RAM installed 4GB

System Type 64-bit operating system, x 64-based processor

Software: MATLAB 2017a

Control Parameter Settings

N=2;	Number of variables
M=50;	Populations size
F=0.1;	Mutation factor
C=0.9;	Crossover rate
I_max=200;	Max iteration time
Run=1;	The number of test time
X_max=[50,50];	Upper bound
X_min=[-50,-50];	Lower bound

The first results are taken before the proposed DE algorithm is implemented.

Output

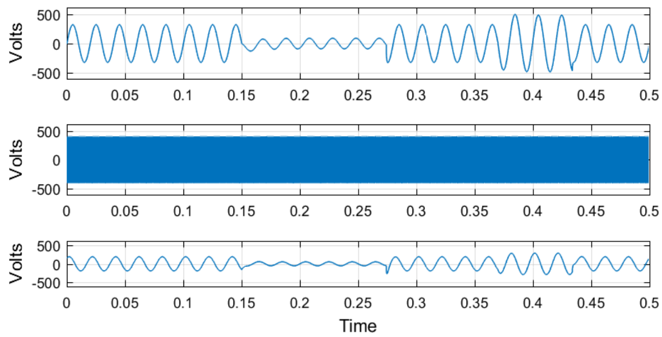


Figure 4.7: Load voltage behavior with DVR disconnected from the system.

Figure 4.7 shows three graphs, the top graph shows the load terminal voltage behavior, the middle graph shows the DVR response to the load voltage and the bottom graph shows the load voltage behavior due to system voltage. It can be noticed that when the system is subjected to the disturbances, the load voltage is affected. On the system it can be seen that voltage sags disturbs the system after 0.15 seconds and lasts up to 0.27 seconds. During that period, the load voltage is also affected with same disturbance for the same period. The next disturbance which is voltage swells is recorded between 0.37 seconds to 0.43 seconds. The load voltage response is the same as of the terminal voltage for the period between 0.37seconds to 0.43 seconds. The DVR response shows maximum response due to the fact that it is not connected to the system, therefore it senses 0 volts from the load because it is not connected to the system.

Output

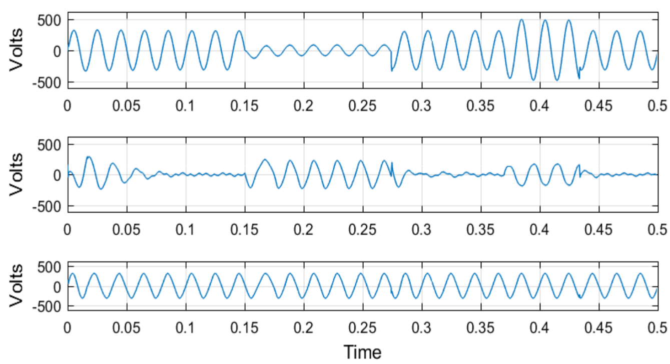


Figure 4.8: Load voltage behavior with DVR connected to the system.

The DVR is connected to the system for the results on Figure 4.8. With the same graph configuration as on Figure 4.7, the same voltage disturbances are recorded on the same periods as on Figure 4.7 when the DVR is connected to the system. It can be noticed that when voltage sags and voltage swell occur, the load voltage is not disturbed due to the compensation voltage and level voltage correction from DVR as soon as it senses voltage imbalance to the system. On the middle graph representing DVR behavior, it can be noticed that when the load voltage is not experiencing any disturbances on the system, the DVR does not inject any compensation voltage or level correction voltage, therefore it reads 0 volts from 0 seconds up to 0.15 seconds, accept for the overshooting it experiences for the first period from 0seconds to 0.06 seconds. From 0.15 seconds to 0.27 seconds it can be noticed that it injects a certain amount of voltage in the same polarity of the operation voltage to compensate for voltage sags. From 0.27seconds to 0.37 seconds it can be noticed going back to 0 volts for that period. From 0.37 seconds to 0.43 seconds it can be noticed that the system experiences voltage swell disturbance. For that period the DVR injects a certain amount of voltage in opposite polarity of the operational voltage in order to oppose a certain amount of overvoltage in the system so that a balanced voltage level is achieved. From 0.43 seconds to 0.5 seconds the DVR falls back to 0 volts again because the system is now healthy.

Following are results of the load voltage behavior based on m.file script coding during the disturbances, voltage sag compensation, voltage swells correction and multi-objectives to be minimized after effects of correction.

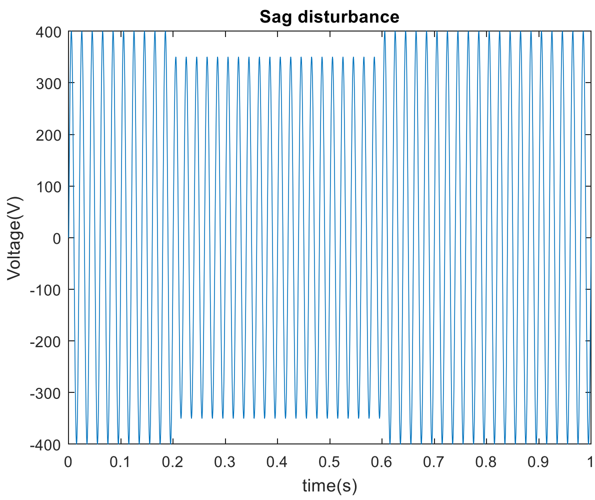


Figure 4.9: Load voltage during voltage sag disturbance.

Figure 4.9 shows the voltage sag disturbance which starts after 0.2 seconds and lasts up to 0.6 seconds, making a period of 0.4 seconds disturbance.

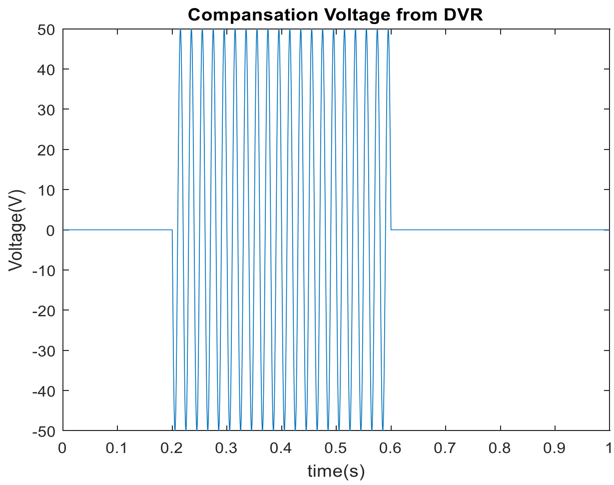


Figure 4.10: Compensation voltage from DVR.

On Figure 4.10, with reference to Figure 4.9, it can be noticed that the compensation voltage of 50 volts is injected to the system to compensate for voltage sags. It can also be noticed that voltage injection starts after 0.2 seconds and lasts up to 0.6 seconds before it falls back to 0 volts injection.

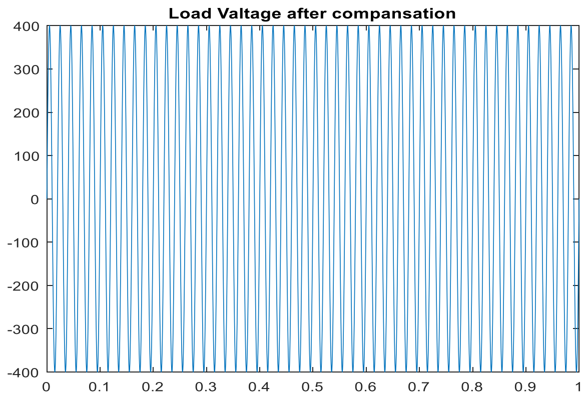


Figure 4.11: Load voltage after compensation.

After voltage compensation DVR, the load voltage goes back to normal operational level as it can be noticed on Figure 4.11.

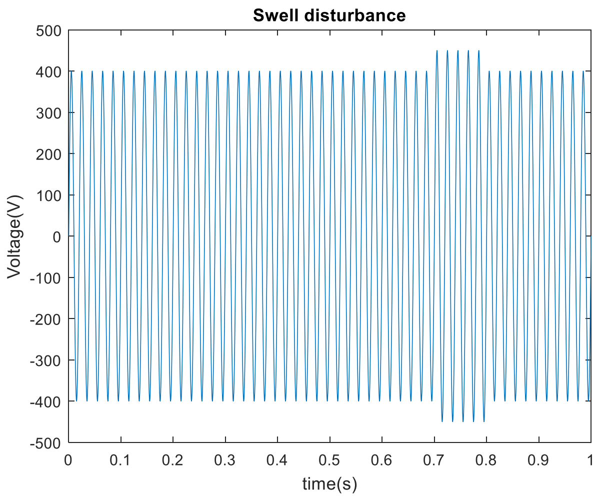


Figure 4.12: Load voltage during voltage swell disturbance.

Figure 4.12 demonstrates the voltage swell disturbance which starts after 0.7 seconds and lasts up to 0.8 seconds, making a period of just 0.1 second disturbance.

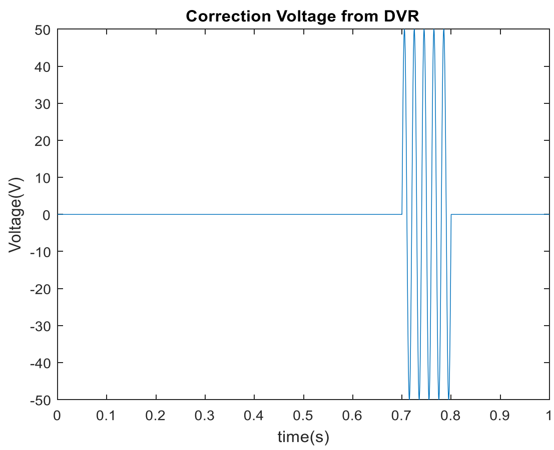


Figure 4.13: Correction voltage from DVR.

Figure 4.13 shows voltage injected from the DVR's transformers in opposite polarity of operational voltage in order to counter-balance the voltage swells. It can also be noticed that the voltage is injected between 0.7 seconds and 0.8 seconds, during which the disturbance is taking place.

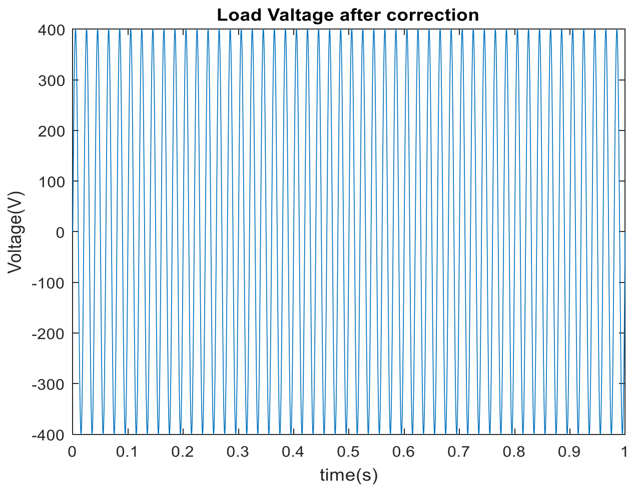


Figure 4.14: Load voltage after correction.

Figure 4.14 shows the operational load voltage after voltage correction by DVR. It can be noticed that after correction the load voltage goes to normal operation, free from disturbances.

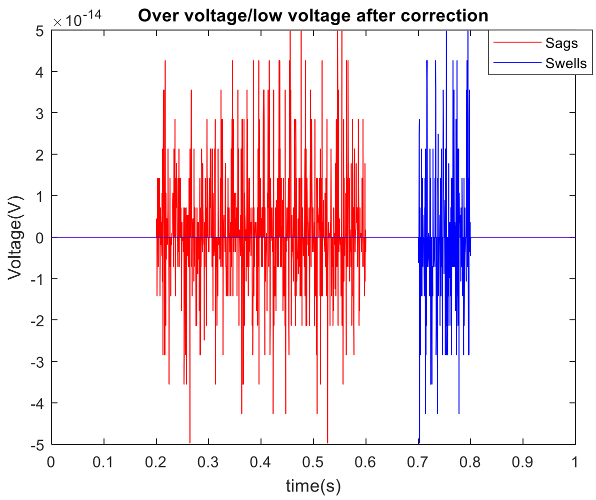


Figure 4.15: Sag and swell effects after voltage correction from DVR.

Figure 4.15 shows the voltage swells and voltage sags effects after compensation and correction on the load voltage. The red painted part represents voltage sags effects while the blue part represents voltage swells effect. The two disturbance effects will be minimized to minimum by evolutionary algorithm in the following stage bellow.

Table 4.1: DE/Rand/1 fitness for Sags and Swells

DE/Rand/1			
Run number	Iteration number	Sags fitness	Swells fitness
1	14	1.057e-11	-6.959e-12
2	18	1.052e-11	-6.935e-12
3	21	1.055e-11	-6.954e-12
4	10	1.052e-11	-6.959e-12
5	14	1.056e-11	-6.959e-12
DE/Modi/2			
Run number	Iteration number	Sags fitness	Swells fitness
1	10	5.234e-12	-5.988e-12
2	11	5.142e-12	-6.837e-12
3	12	5.376e-12	-6.309e-12
4	9	5.322e-12	-6.731e-12
5	10	5.334e-12	-6.745e-12
DE/Modi/3			
Run number	Iteration number	Sags fitness	Swells fitness
1	5	4.902e-12	-6.625e-12
2	6	4.717e-12	-6.322e-12
3	7	4.873e-12	-6.249e-12
4	3	4.744e-12	-5.995e-12
5	5	4.903e-12	-6.790e-12

Based on the results of DE/rand/1, it can be noticed that both voltage swell and voltage sag minimization occurs at same number of iterations. It can also be noticed that for voltage swell optimization, the minimization starts from more positive side going more negative which indicates the counter-balancing of over-voltage with opposite polarity injected voltage to the system. For voltage sag optimization it can also be noticed that the minimization goes more positive as an indication of compensating for low voltages on the system. On results from DE/Modi/2, it is observed that the optimization process is the same as on DE/rand/1 results accept that there is improvement achieved. The convergence is quicker compared to the one of DE/Rand/1. On the results obtained on DE/Modi/3, it is noticed that the iterations were convergence occurs are a bit more compared to the ones on DE/Modi/2, but are better compared to the ones of classical DE/Rand/1. Swells and Sags fitness for DE/Modi/3 is achieved between 9 to 12 iterations, DE/Modi/2 is between 3 and 7 iterations and for DE/Rand/1 is between 10 and 21 iterations

Table 4.2: Statistical Data Analysis

Mutation strategy	Best	Average	Worse
DE/Rand/1	2	2	1
DE/Modi/2	4	1	0
DE/Modi/3	4	1	0

Based on statistical data with regards to convergence against number of iteration, it is noticed that classical DE/Rand/1 has 40% best convergence, 40% average convergence and only 20% worse convergence. For DE/Modi/2 and DE/Modi/3, their convergence is excellent with both having 80% best convergence, 20% average convergence and 0% worse convergence.

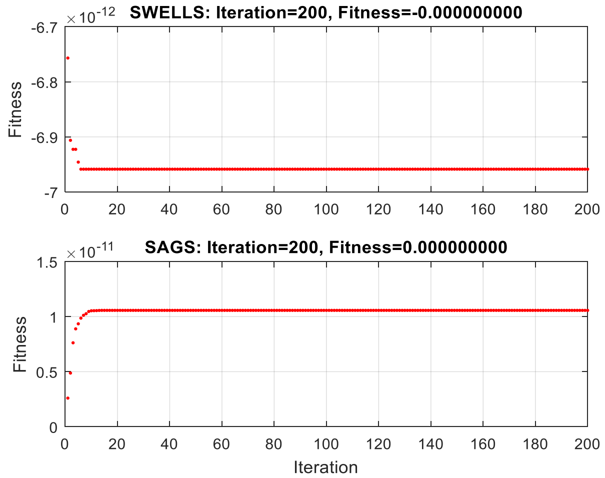


Figure 4.16: Multi-objective minimization based on DE/Rand/1

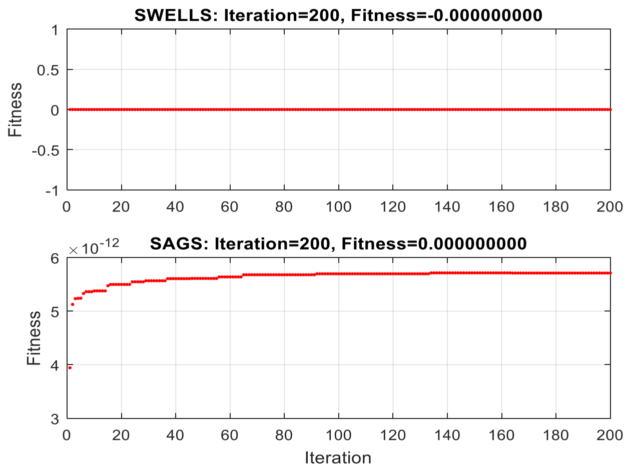


Figure 4.17: Multi-objective minimization based on DE/Modi/2

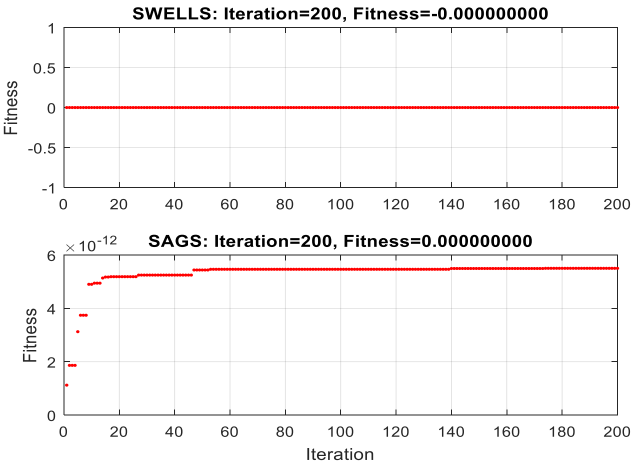


Figure 4.18: Multi-objective minimization based on DE/Modi/3

4.6. conclusion

Based on the simulation results obtained, it is observed that DVR plays the most important role in minimizing power disturbances in the power systems. It is noticed that the DVR does not take part in the power network when the operational load voltage is normal, it only takes part when it senses operational disturbance from the sensitive load. Then it would do the compensation for voltage sags if the disturbance involves under-voltage operation or it would do voltage correction if the disturbance involves voltage swells. Therefore it does not waist electric power unnecessary instead it operates efficiently. It can also be noticed that Improved Differential Evolution is able to do multi-objective optimization efficiently and without experiencing any cease of simulation flow and conflict amongst the two objective functions. The proposed DE achieved strong and effective convergence in less than 13 iterations. That indicates efficiency, effectiveness of the improved DE. During voltage disturbances optimization it is noticed that the voltage disturbances were minimized up to as minimum as 5.234e-11 volts for voltage sags and up to as minimum as -6.873 volts for voltage swells and the mutation strategies were consistence with regards to iterations were convergence occurs, therefore making the Improved DE suitable for power quality optimization in smart grid. It can be concluded that the inclusion of DVR and improved DE in smart grid can achieve a better power quality that is effective to the sensitive loads and malfunction and damage to electric equipment by poor power quality can be minimized.

CHAPTER 5

CONCLUSION AND FUTURE WORKS

5.1. Conclusion

The research objective was to attempt to solve power quality problems in smart grid on the basis of application of enhanced based populated stochastic evolutionary algorithm named Differential Evolution by means of modified mutation schemes and by application of dynamic voltage restorer. Under enhancement of differential evolution, three modifications of DE mutation schemes were developed, DE/Modi/1, DE/Modi/2 and DE/Modi/3 with reference from classical DE/Rand/1 mutation scheme. Only DE/Modi/2 and DE/Modi/3 modifications proved success during simulation experiment due to meeting the objectiveness of the experiment which was to overcome stagnation of DE during simulation and to improve DE's convergence speed. During simulation experiment done on eight benchmark functions including Bukin function and Griewank function, it was discovered that classical DE/Rand/1 was not able to optimize Bukin and Griewank to optimum point and the optimization lacked convergence speed. With modified DE/Modi/2 and DE/Modi/3 in place, Bukin and Griewank functions were optimized to optimum point and their convergence speed improved swiftly making 84.72% and 81.95% of the best convergence time respectively. It was also discovered that mutation factor crossover rate F/C combination of 0.1/0.9 also helped the modified DE/Modi/2 and DE/Modi/3 on their success with regards to achieving best optimization results during experiment. Both DE/Modi/2 and DE/Modi/3 proved to be robust, fast and effective when compared to classical DE/Rand/1, deeming the experiment successful for DE improvement.

For the application of the improved differential evolution on attempt to solve power quality in smart grid, two objective functions were lined up to be minimized. Voltage sags and voltage swells were the obstacles in power quality. DVR application was introduced to solve the voltage swells and sags problems and multi-objective optimization technique called for optimization of the two objective functions. Parallel operation multi-objective technique was developed to attempt to solve the two objective functions without causing conflict with each other. During the DVR application experiment it was discovered that DVR is the most efficient power compensator due to the fact that it does not take part in the power network when the operational load voltage is normal, it only takes part when it senses operational disturbance from the sensitive load. It was also discovered that during multi-objective optimization in parallel operation, the objective functions are optimized in parallel and therefore minimizing chances of them being in conflict during optimization. Overall it can be concluded that the research has achieved effective improvement of power quality in smart grid by employing DVR and improved Differential evolution, thereby minimizing voltage sags and voltage swells, which can be beneficial to households and manufacturing industries by reducing the number of damages to electrical appliances and electrical equipment.

5.2. Future works

More research can be done to improve Differential Evolution such as auto scaling of control parameters by making a hybrid of Differential Evolution and Particle swarm optimization. Other researches that can be done to optimize smart grid's integration of renewable energy sources is making an enhanced control system for attempt to generate bigger watts from natural resources and make portable energy grids based on renewables for households and hospitals in order to reduce the use of diesel generators for emergency backup. The other research that can be done is introducing smart locomotives that will make the employment of renewable energy sources such as solar and wind turbines to operate. That will reduce energy costs from diesel and electricity from electric utilities.

PUBLICATIONS

1. Saveca, J., Wang, Z. & Sun, Y. (2018) Improved Differential Evolution Based on Mutation Strategies. *Lecture Note in Computer Science*, Springer,Cham, Volume 10941. 233-242.

2. Saveca, J., Wang, Z. & Sun, Y. (2019) Dynamic Voltage Restorer Based Power Quality Optimization Using Improved Differential Evolution Algorithm. *International Conference on Sustainable Materials Processing and Manufacturing, SMPM 2019*, Sun City Resort, South Africa, 08 – 10 March 2019. Submitted to ScienceDirect Elsevier.

REFERENCES

Adekoya, A. R. & Helbig, M. (2017) A Differential Evolution Algorithm for Dynamic Multi-Objective Optimization. *Congress on Evolutionary Computation (CEC).* 1-10.

Akhtar, Z., Chaudhuri, B. & Hui, S.H.R. (2017) Smart Loads for Voltage Control in Distribution Networks. *Journal of IEEE TRANSACTIONS ON SMART GRID*. Volume 8. Issue 2. 1-10.

Agarwal, V. & Tsoukalas, L.H. (2011) Smart Grids: Importance of Power Quality. In: Hatziargyriou, N. et al. (Eds.) E-Energy 2010. *Institute for Computer Sciences, Social Informatics and Telecommunications Engineering 2011*. LNICST 54. PP. 136–143, 2011.

Annaswamy, A., Ed., (2013) Vision for Smart Grid Control: 2030 and Beyond. In: Piscataway, NJ, USA: IEEE Standards Association, Jun. 2013.

Arora, Y. A. (2014) Review on Power Quality problems and its solution at distribution end using Different interfacing devices and Distributed Generation. In: *Journal of Emerging Trends in Engineering and Development*. Volume 5. Issue 4. 373-382.

Atasoy, T., Akinç, H. E. & Erçin, O. (2017) An Analysis on Smart Grid Applications and Grid Integration of Renewable Energy Systems in Smart Cities. 4th *International Conference on Renewable Energy Research and Applications.* 547-550.

Athan, T.W. & Papalambros, P.Y. (1996) A note on weighted criteria methods for compromise solutions in multi-objective optimization. *Eng. Optim*. Volume 27, 155–176

Bansal, J.C. & Gopal, A. (2016) Stability Analysis of Differential Evolution. *Journal of Workshop on Computational Intelligence*. 221-223.

Bollen, Math H.J. (1999) Solving power quality problems : voltage sags and interruptions. New York: IEEE Press. 139. ISBN 978-0-7803-4713-7.

Bingham, R.P. (1998) *Sags and Swells*. Dranetz-BMI. (September 1994) 1-22.

Brumsickle,W. E., Schneider, R. S., Luckjiff, G. A., Divan, D. M., and McGranaghan, M. F. (2001). Dynamic sag correctors: cost-effective industrial power line conditioning. *IEEE Transactions on Industry Applications.* Volume 37, Issue 1, 212–217.

Buccella, C., Cecati, C., Ergut, S., Gungor, V.C., Hancke, G.P., Kocak, T., Member, S. & Sahin, D(.2013) A Survey on Smart Grid Potential Applications and Communication Requirements. *Journal of IEEE transactions on Industrial Informatics*. Volume 9. Issue 1. 28–42.

Bush, S.F. (2013) Information Theory and Network Science for Power Systems. In: Goel, S., Bush, S. F., Bakken, D. (eds) *Chapter in IEEE Vision for Smart Grid Communications: 2030 and Beyond*. New York: IEEE Press.

Bush, S.F. (2014) Network Theory and Smart Grid Distribution Automation. In: *Journal of IEEE selected areas in communications*, Volume 32. Issue 7. 1451-1459.

Buxton. R. (1998) Protection from voltage dips with the Dynamic voltage restorer. *Proc. IEEE colloquium on Dynamic voltage restorers replacing those missing cycles*, Volume 3, Issue 6, 1-3.

Capriglione, D., Ferrigno, L., Paciello, V., Pietrosanto, A., Vaccaro, A. (2016) Experimental characterization of consensus protocol for decentralized smart grid metering, *Measurement*. Elsevier Ltd. Volume 77. 292 - 306.

Caramia, M. & Dell'Olmo, P. (2008) Multi-Objective Optimization. Multi-Objective Management in Freight Logistics, London, U.K,: Springer, pp. 11-36.

Casolino, G. M., Di Fazio, A. R., Losi, A., Russo, M. & De Santis, M. (2017) A Voltage Optimization Tool for Smart Distribution Grids with Distributed Energy Resources", *IEEE International Conference on Environment and Electrical Engineering (EEEIC 201*7).1-6.

Castilla, M., de Vicuña, L.G., Guerrero, J. M., Matas, J. & Miret, J. (2006) Wireless-Control Strategy for Parallel Operation of Distributed-Generation Inverters. *Journal of IEEE Transactions on Industrial Electronics*. Volume 53. Issue 5. 1461-1470.

Ceaki, O., Mancasi, M., Seritan, G. & Vatu, R. (2017) Analysis of Power Quality Improvement in Smart Grids. In: ATEE 2017: *The 10th International Symposium on Advanced Topics in Electrical Engineering,* 23-25 March 2017, Bucharest, Romania. IEEE. PP. 797-801.

Chattopadhyay, S., Sanyal, S. K. & Chandra A. (2011) Comparison of various mutation schemes of differential evolution algorithm for the design of low-pass FIR filter, 809-814.

Chaves-Gonz´alez, J. M. & P´erez-Toledano, M. A. (2015) Differential evolution with pareto tournament for the multi-objective next release problem. *Applied Mathematics and Computation*, Volume. 252, 1–13.

Chauhan, D. P. S., Madariya, M., Prakash, T. & Singh, V. P. (2016) Optimization with Improved Differential Evolution Algorithm having Variable Tolerance. In: IEEE 2016: *Second International Conference on Computational Intelligence & Communication Technology, 2016,* Raipur, India. IEEE. PP. 270-274.

Chen, L., Dall'Anese, E., Tian, J. & Zhou, X. (2016) Local Voltage Control in Distribution Networks: A Game-Theoretic Perspective. *Journal of 2016 North American Power Symposium* (NAPS). 1-6.

Chen, S., Lu, W., Yan, X., Zhang, Y. & Zhou, M 2017. Influence on Low-voltage Surge Protective Devices of Overhead Distribution Lines Due to Nearby Return Strokes. *Journal of IEEE Transactions on Power Delivery*. Volume 8977. Issue c, 1–8.

Chen,W., Sahai, A., Messac, A. & Sundararaj, G. (2000) Exploration of the effectiveness of physical programming in robust design. J. Mech. *Des*. Volume 122, 155–163.

Danbumrungtrakul, M., Saengsuwan, T., & Srithorn, P. (2017) Evaluation of DVR Capability Enhancement-Zero Active Power Tracking Technique. *IEEE Access*. Volume 5, 10285–10295.

Delincé, F. & Schipman, K. (2010) The importance of good power quality. ABB. Report number: 1.

Dell'Aquila, A., Kerekes,T., Liserre, M. & Mastromauro, R.A. (2009) A Single-Phase Voltage Controlled Grid Connected Photovoltaic System with Power Quality Conditioner Functionality. *Journal of IEEE Transactions on Industrial Electronics*. Volume 56. Issue 11. 4436-4444.

Devalalitha, C. & Vijayakumar, R. (2014) Selective Harmonic Elimination PWM Method Using Two Level Inverter by Differential Evolution Optimization Technique. *Journal of Science, Engineering and Management Research*. 1-6.

Dhomane, G. A., Jolhe, S.P. & KaraIkar M. D. (2016). Smart Grid and Power Quality (PQ) Issues. *Journal of Green Engineering and Technologies* 5–7.

Di Santo, K. G., Di Santo, S. G., Monaro, R. M., Marco Antonio Saidel, M. A. (2017) Active demand side management for households in smart grids using optimization and artificial intelligence. , *Measurement*. Elsevier Ltd Volume 115. 152–161.

Dugan, R. C., McGranaghan, M. F., Beaty, H. W. & Santoso, S. (2004*) Electrical Power Systems Quality*. Second Edition, McGraw-Hill. Available from: http://www.digitalengineeringlibrary.com [accessed 27 August 2018].

Edomah, N. (2009) Effects of Voltage Sags, Swell and Other Disturbances on Electrical Equipment and Their Economic Implications In:. *20th International Conference on Electricity Distribution, CIRED*, p1-4.

Fang, G. X, Jie, L. (2016) An Improved Differential Evolution Algorithm for Unconstrained Optimization Problems. *Journal of Computational Intelligence and Security*. 179-181.

Faranda, R. & Hafezi, H. (2016) Single-Phase Dynamic Voltage Conditioner Control under Load Variation. 563–568.

Ganbavale, M. P. (2014) Differential Evolution Using Matlab. Birla Institute of Technology and Science, Pilani. Hyderabad Campus. 1-6.

Ghosn, S. B., Loegering, D., Mcculloch, R. & Nygard, K. E. (2011) Optimization Models for Energy Reallocation in a Smart Grid, 186–190.

Grogg, K. (2005) Harvesting the Wind: The Physics of Wind Turbines. Department of Physics and Astronomy, Carleton College.

Gungor, V. C., Buccella, C., Cecati, C., Ergüt, S., Hancke, G. P., Kocak, T. & Sahin, D. (2011) Smart Grid Technologies: Communication Technologies and Standards. *IEEE Transactions on Industrial Informatics.*, Volume. 7, Issue 4, 529–539.

Gungor, V. C., Lu, B. & Hancke, G. P., (2010) Opportunities and challenges of wireless sensor networks in smart grid. *IEEE Trans. Ind. Electron.*, Volume. 57, Issue 10, 3557–3564.

Han, Y., Jiang, X., Wang, J., Yang, S. (2016) Dynamic Spectrum Allocation Algorithm Based on Matching Scheme for Smart. *Journal of computer and communications*. 3015-3019.

Hojabri, M. & Toudeshki, A. (2013) Power Quality Consideration for Off-Grid Renewable Energy Systems. *Journal of Energy and Power Engineering*. Volume 5. 377–383.

Horsley, T. & Seymour, J. (2008) The seven types of power problems. *Journal of Engineer IT*. 60–65.

Hosenuzzaman, M., Rahim, N. A., Selvaraj, J., Hasanuzzaman, M. Malek, A. B. M A. & Nahar, A. (2015) Global prospects, progress, policies, and environmental impact of solar photovoltaic power generation. *Renewable & Sustainable Energy Reviews*. Volume 41, Issue 0, 284–297.

Iyer, R. K., Mukerjee R.N., Ramachandaramuthy, V. K. & Ramasamy, A. K. (2005) Dynamic Voltage Restorer For Voltage Sag Compensation. *Journal of Power Quality Research Group*. 1289–1294.

Jung, D. Kim, J.H., Lee, H.M. & Sadollah, A. (2017) Engineering Benchmark Generation and Performance Measurement of Evolutionary Algorithms. 714-717.

Kagan, N. & Paulo, S. (2016) Bio-inspired Metaheuristics Applied to Volt/VAr Control Optimization Problem in Smart Grid Context. 295–300.

Kanjiya, P. & Khadkikar, V. (2013) Enhancing Power Quality and Stability of Future Smart Grid with Intermittent Renewable Energy Sources Using Electric Springs. *International Conference on Renewable Energy Research and Applications*. 918-922.

KarthiKeyan, K., Kumar, M.A.B., Palani, M., Prabhu, N.A., Subbaiah, P., Sujatha, K. & Sundaram, M.M. (2016) Automatic Tap Changing in Transformers for Power Quality Enhancement in a Smart Grid Distribution System. In: IEEE 2016*: International Conference on Electrical, Electronics and Optimization Techniques (ICEEOT)-2016,* IEEE. PP. 4458-4463.

Khalghani, M.R., Khooban, M.H. & Shamsi-nejad, M.A. (2014) Dynamic voltage restorer control using bi-objective optimization to improve power quality's indices. *Journal of IET Science, Measurement & Technology*. 203–213. DOI: 10.1049/iet-smt.2013.0084.

Khanna, A. (2012) Smart Grid, Smart Controllers and Home Energy Automation—Creating the Infrastructure for Future. In: *Smart Grid and Renewable Energy,* Science Research, 165-174.

Lampinen, J.A., Price, K.V. & Storn, R.M. (2005) *Differential Evolution A Practical Approach to Global Optimization.* Berlin, Springer.

Lampinen, J. & Zelinka, I. (2000) On Stagnation of Differential Evolution Algorithm. *International Conference on Soft Computing.* 76-82

Laverty, D.M., Morrow, D. J., Best, R. & Crossley, P. A. (2010) Telecommunications for smart grid: Backhaul solutions for the distribution network. *IEEE Power and Energy Society General Meeting*. 1–6.

Leon, M., Xiong, N. (2014) Investigation of Mutation Strategies in Differential Evolution for Solving Global Optimization Problems. *Artificial Intelligence and Soft Computing.* Lectures Note in Computer Science. Volume 8467, 372-383.

Lewis, R. P., Igic, P. & Zhongfu, Z. (2009) Assessment of communication methods for smart electricity metering in the U.K. *IEEE PES/IAS Conf. Sustainable Alternative Energy (SAE)* .1–4.

Lezama, F., Rodrıguez-Gonz´alez, A. Y. & de Cote, E. M. (2016) Load Pattern Clustering Using Differential Evolution with Pareto Tournament. *Congress on Evolutionary Computation (CEC)*. 241- 248.

Liftarn(talk).(2009)*Blackout.*http://www.Commons.m.wikimedia.org/wiki/File:PowerOutage Blackout.svg#mw-jump-to-license.com [accessed 28 August 2018].

Melhem, F. Y., Grunder, O., Hammoudan, Z. & Moubayed N. (2018) Energy Management in Electrical Smart Grid Environment Using Robust Optimization Algorithm, IEEE *Transactions on Industry Applications*, Volume. 54, Issue 3, 2714-2726.

Messiha, M. A., Maraket, C. F., Massoud, A., MIqbal, A. & Soliman, R. (2017) Voltage Sag Mitigation Employing Dynamic Voltage Restorer with Minimum Eneregy Requirements: Analysis and Implementation. 1-6.

Meyer, C., De Doncker, R. W., Li, Y. W., and Blaabjerg, F. (2008) Optimized control strategy for a medium-voltage DVR—Theoretical investigations and experimental results. *IEEE Transactions on Power Electronics*. Volume 23, Isuue6, 2746–2754.

Nygard, K. E. & Ranganathan, P. (2011) Optimization models for energy reallocation in a smart grid. In: IEEE 2011*. Conference on Computer Communications Workshops (INFOCOM WKSHPS)-2011,* IEEE-2011. PP. 432-439.

Odero, N. & Okinda, V. (2016)Modelling, Simulation and Optimal Sizing of a Hybrid Wind, Solar PV Power System in Northern Kenya. *Journal of renewable energy research*. Volume 6. Issue 4. 377-383.

Okwu, P. I., Okolo C. C., Obinna, O., Matthew, D. O, & Uche, A. (2017) Details of Photovoltaic Solar System Design Calculations and the Accessories. *Journal for Research in Applied Science & Engineering Technology (IJRASET)*. Volume 5, Issue 4, 2933-2938.

Opara, K., & Arabas, J. (2017) Comparison of mutation strategies in differential Evolution-a probabilistic perspective. *Journal of Swarm and Evolutionary Computation*, Elsevier B.V, Volume 338, 1-37.

Penunuri, F., Cab, C., Tapia, J. A. & Zambrano-Arjona, M. A. (2015)A study of the Classical Differential Evolution control parameters. *Swarm and Evolutionary Computation*, Elsevier B.V Volume 26, 86-96.

Peizhong, Y., Iwayemi, A. & Zhou, C. (2011) Developing ZigBee Deployment Guideline Under WiFi Interference for Smart Grid Applications, IEEE Transaction on Smart Grid, Volume 2, Issue 1, 110–120.

Phuangpornpitaka, N. & Tiab, S. (2013) Opportunities and Challenges of Integrating Renewable Energy in Smart Grid System. *Journal of 10th Eco-Energy and Materials Science and Engineering Symposium*. Energy Procedia 34 (2013). 282-290.

Remya, V. K., Parthiban, P., Ansal, V. & Chitti-Babu, B. (2018) Dynamic Voltage Restorer (DVR) – A Review. *Journal of Green Engineering*. River Publishers Volume. 8, Issue4, 519–572.

Reyes-Sierra, M. & Coello, C. C. (2006) Multi-objective particle swarm optimizers: survey of the state-of-the-art," *International journal of computational intelligence research*, Volume. 2, Issue 3, 287-308.

Sagoo, S. (2012) Array Failure Correction Using Different Optimization Technique, 2012.

Samad, T. & Annaswamy, A. M. (2017) Controls for Smart Grids: Architectures and Applications. *Proceedings of the IEEE*, Volume 105, Issue 11, 2244-2261.

Sarker, R. A., Elsayed , S. M. & Ray T., (2014) Differential Evolution Dynamic Parameters Section for Optimization Problems. *IEEE Transactions on Evolutionary Computation*, Volume 18, 689-707.

Saveca, J., Wang, Z. & Sun, Y. (2018) Improved Differential Evolution Based on Mutation Strategies. *Lecture Note in Computer Science*, Springer,Cham, Volume 10941. 233-242.

Saveca, J., Wang, Z. & Sun, Y. (2019) Dynamic Voltage Restorer Based Power Quality Optimization Using Improved Differential Evolution Algorithm. *International Conference on*

Sustainable Materials Processing and Manufacturing, SMPM 2019, Sun City Resort, South Africa, 08 – 10 March 2019. Submitted to ScienceDirect Elsevier

Short, T. A. (2004) Electric Power Distribution Handbook. Boca Raton, London, New York & Washington, D.C. CRC Press LLC. ISBN 08493-1791-6.

Subhalakshmipriya, C. & Suganya, U. (2015) Smart-Grid in Electrical & Electronical Communication Technology. *Journal of Engineering Research and General Science*. Volume 3. Issue 1. 3(1), 386–393.

Suganthi, S.T., Devaraj, D., HosiminThilagar, S. & Ramar K. (2016) Improved Multi Objective Differential Evolution Algorithm for Congestion Management in Restructured Power Systems. *Congress on Evolutionary Computation*, 203-210.

Tayal D. & Gupta C. (2012) A new scaling factor for Differential Evolution Optimization. *National Conference on Communication Technologies & its impact on Next Generation Computing CTNGC2012 Procceedings*, IJCA, 1-5.

Thakur, P., & Singh, A. K., (2017) A novel method for joint characterization of unbalanced voltage sags and swells*, Int Trans Electr Energ Syst*. 1-10.

Thangaraj R., Pant, M. & Abraham, A. (2010) New mutation schemes for differential evolution algorithm and their application to the optimization of directional over-current relay settings. *Journal of Applied mathematics and computation* Elsevier B. V, Volume 216, 532-544.

Wan, C., Zhao, J., Song, Y., Xu, Z., Lin, J. & Hu, Z. (2015) Photovoltaic and Solar Power Forecasting for Smart Grid Energy Management. *Journal of Power and Energy Systems.* Volume 1, Issue 4, 38-46.

Wu, Y., Lee, W. & Chien, C. (2011) Modified the Performance of Differential Evolution Algorithm with Dual Evolution Strategy. *International Conference on Machine Learning and Computing IPCSIT*. Volume 3, Issue1, 57-63.

Wu, G., Shen X., Chen H., Lin, A. & Suganthan, P. N. (2017) Ensemble of differential evolution variants*. Journal of Information Sciences*, Elsevier B.V., Volume 423 172-186.

Zhang, Q., Wang, M., Wang, X. & Tian, S. (2017) Mid-long Term Optimal Dispatching Method of Power System With Large Scale Wind-Photovoltaic-Hydro Power Generation. IEEE. 1-6.

Zheng, L. M., Zhang, S. X., Tang, K. T. & Zheng S. Y. (2017) Differential evolution powered by collective information. *Journal of Information Sciences* Elsevier B.V, Volume 399, 13-29.

APPENDICES

Appendix A: DE matlab code for improved DE based on mutation Strategies:

```
% Improved Differential Evolution Based on Mutation
Strategies% For Smart
% Grid Optimization. %%Main Code%%

clear all
    clc
tic
    %Common Parameter Setting
    N=2;          % Number of variables
    M=50;         % Populations size
    F=0.5;        % Mutation factor
    C=0.9;        % Crossover rate
    I_max=200;    % Max iteration time
    Run=1;        % The number of test time
    X_max=[5.12,5.12];
    X_min=[-5.12,-5.12];
    ibest=1;

    Func=@Rastrigin;


    % 2.The whole test loop
    for r=1:Run
        iter=0;
        % 1.Generate MxN matrix
        for m=1:M
            for n=1:N
                X(m,n)=X_min(n)+rand()*(X_max(n)-X_min(n));
            end
        end


        for i=1:I_max   % Stop when the iteration large than
the max iteration time

            iter=iter+1;
            for m=1:M % For each individual
                % Mutation
                [V]=rand1(X,M,F,m);
                % Check if the element in the V matrix beyond
the boundary.
                for n=1:N
                    if V(1,n)>X_max(1,n)
                        V(1,n)=X_max(1,n);
                    end
                    if V(1,n)<X_min(1,n)
```

```
                V(1,n)=X_min(1,n);
            end
        end

        % Crossover put the result in the U matrix
        jrand=floor(rand()*N+1);
        for n=1:N
            R1=rand();
            if (R1<C || n==jrand)
                U(1,n)=V(1,n);
            else
                U(1,n)=X(m,n);
            end
        end

        % Selection
        if Func(U(1,:)) < Func(X(m,:))
            Tr=U(1,:);
            else
            Tr=X(m,:);
        end
        % Use the selection result to replace the m
row
        X(m,:)=Tr;

        % Evaluate each individual's fitness value,
and put the result in the Y matrix.
        Y(m,1)=Func(X(m,:));

    end % Now the 1th individual generated

    % Select the lowest fitness value
    [y,ind1]=sort(Y,1);
    Y_min=y(1,1);
    [Ymin,ind] = min(Y);

    % plot the picture of iteration
    figure(2);
    plot(iter,Ymin,'r.');
    xlabel('Iteration');
    ylabel('Fitness');
    title(sprintf('Rastrigin: Iteration=%d,
Fitness=%9.9f',i,Ymin));
    grid on;
    hold on;

end % Finish I_max times iteration

hold off;
PlotR();
hold on;
```

```
        scatter3(X(ind,1),X(ind,1),Ymin,'fill','ro');

    end % Run 30 times
    toc
```

DE/Modi/3 coding

```
% DE/Modi/3 Code%

function [V]=rand1(X,M,F,m)

    R=randperm(M);
    j=R(1);
    k=R(2);
    p=R(3);
    u=R(4);
    v=R(5);
    if j==m
       j=R(6);
    elseif k==m
       k=R(6);
    elseif p==m
       p=R(6);
    elseif u==m
       u=R(6);
    elseif v==m
       v=R(6);
    end
    V=(((X(j,:)).^2)*F)/2+F*(X(k,:)-X(p,:
```

Rastrigin’s Function

```
% Rastrigin's Benchmark Function

function y = Rastrigin (X)
    % Rastrigin's Function
    A = 10;
    n = 2;
    m = 0;

    for i = 1:n
        m = m + X(i)^2 - A*cos(2*pi*X(i));
    end

    y = 10*n + m;

end
```

Rastrigin's Plot

```
%Rastrigin's Plot%

function PlotR()

[X,Y] = meshgrid(-5.12:0.03:5.12,-5.12:0.03:5.12);
N = size(X,1);

for i = 1:N
    for j = 1:N
        z = [X(i,j),Y(i,j)];
        Z(i,j) = Rastrigin(z);
    end
end

figure(1);
mesh(X,Y,Z);
title('Rastrigin Function in 2 dimension');
axis([-5.5 5.5 -5.5 5.5 0 80]);

end
```

Ackley Function

```
function y = Ackley(x)
      n=2;
      sum1 = 0;
      sum2 = 0;

      for i = 1:n
          sum1 = sum1 + x(i)^2;
          sum2 = sum2 + cos((2*pi) * x(i));
      end

      y = 20 + exp(1)-20*exp(-0.2*sqrt(1/n*sum1))-
exp(1/n*sum2);

end
```

Bukin Function

```
function y = bukin (x)
    % bukin's Function

    x1= x(1);
    x2= x(2);

    term1 = 100*sqrt(abs(x2-0.01*x1^2));
    term2 = 0.01*abs(x1+10);
```

```
    y = term1+term2;

end
```

Griewank Function

```
function y = Griewank(x)

        n = 2;
        fr = 4000;
        s = 0;
        p = 1;

        for i = 1:n
            s = s + x(i)^2;
            p = p * (cos((x(i))/(sqrt(i))));
        end

        y = (s/fr)-p+1;

end
```

Schwefel Function

```
function y = schw(x)

%
n = 2;
s = 0;
p = 0;

for i = 1:n
    s = s + abs(x(i));
    p = p + abs(x(i));
end

y = s + p;

end
```

Sphere Function

```
function y = Sphere (x)

      n = 2;
```

```
        sp = 0;


        for i = 1:n
            sp = sp + x(i)^2;

        end

        y = sp;
end
```

Sum-power Function

```
function y = SumPower (x)

        n = 2;
        sp = 0;


        for i = 1:n
            sp = sp + abs(x(i)).^(i+1);

        end

        y = sp;
end
```

Sum-Power Function

```
function y = SumSquuare (x)

        n = 2;
        sp = 0;


        for i = 1:n
            sp = sp + i*x(i)^2;

        end

        y = sp;
end
```

Appendix B: DVR Power Quality Optimization

```
%POWER QUALITY OPTIMIZATION IN SMART GRID BASED ON IMPROVED
DIFFERENTIAL
%EVOLUTION
clear;
close all;
clc;
V_nom= 400;     % Normal voltage before fault
Ang_nom= 60;    %phase angle(phase angle in degree b4 fault)
Ang_pr=Ang_nom*pi/180;
V_r=V_nom*cos(Ang_pr);
V_i=V_nom*sin(Ang_pr);
freq = 50; %frequency in Hz;
freq_RPS=2*pi*freq;
V_f=50;

t=0:0.0005:1;
V_L=V_nom*sin(freq_RPS*t);
figure(1)
plot(t,V_L)
xlabel('time');
ylabel('Voltage(V)');
title('Normal Voltage');



 % input voltage and phase angle after fault.
 %voltage magnitude after fault.


V_sag=((V_nom-V_f.*((heaviside(t-0.20)-heaviside(t-
0.60))))).*sin(freq_RPS*t);
figure(2)
plot(t,V_sag);
xlabel('time(s)');
ylabel('Voltage(V)');
title('Sag disturbance');

V_comp =((-V_f*((heaviside(t-0.20)-heaviside(t-
0.60))))).*sin(freq_RPS*t);
figure(3)
plot(t,V_comp)
xlabel('time(s)');
ylabel('Voltage(V)');
title('Compansation Voltage from DVR');

V_ok1 = V_sag - V_comp;
figure(4)
plot(t,V_ok1)
xlabel('time(s)');
```

```
ylabel('Voltage(V)');
title('Load Valtage after compansation');

V_dip = V_L - V_sag;
%figure(5)
%plot(t,V_dip,'Color',[0 0.7 0])

%Fault due to Voltage swell to the system.

V_L_swell=((V_nom+V_f*((heaviside(t-0.70)-heaviside(t-
0.80))))).*sin(freq_RPS*t);
figure(6)
plot(t,V_L_swell);
xlabel('time(s)');
ylabel('Voltage(V)');
title('Swell disturbance');
%swell wave

V_c = 50;
V_L_co = V_c*((heaviside(t-0.70)-heaviside(t-
0.80))).*sin(freq_RPS*t);
figure(7)
plot(t,V_L_co);
xlabel('time(s)');
ylabel('Voltage(V)');
title('Correction Voltage from DVR');

V_ok1 = V_L_swell - V_L_co;
figure(8)
plot(t,V_ok1);
xlabel('time(s)');
ylabel('Voltage(V)');
title('Load Valtage after correction');

V_swell = V_L - V_L_swell;

J1 = V_dip + V_comp;


J2 = V_swell + V_L_co;

figure(9)
plot(t,J1,'r',t,J2,'b-')
xlabel('time(s)');
ylabel('Voltage(V)');
title('Over voltage/low voltage after correction');
```

```
% Multi-objective Differential Evolution Based on Parallel
Operation
% Technique%

tic
    clear
    close all
    clc
    %Common Parameter Setting
    N=2;         % Number of variables
    M=50;        % Populations size
    F=0.1;       % Mutation factor
    C=0.9;       % Crossover rate
    I_max=200;   % Max iteration time
    Run=1;       % The number of test time
    X_max=[50,50];
    X_min=[-50,-50];

  Func1=@sags;
  Func=@swell;

    % 2.The whole test loop
    for r=1:Run
        iter=0;
        % 1.Generate MxN matrix
        for m=1:M
            for n=1:N
                X(m,n)=X_min(n)+rand()*(X_max(n)-X_min(n));
            end
        end


        for i=1:I_max   % Stop when the iteration large than
the max iteration time

            iter=iter+1;
            for m=1:M % For each individual
                % Mutation
                [V]=rand1(X,M,F,m);
                % Check if the element in the V matrix beyond
the boundary.
                for n=1:N
                    if V(1,n)>X_max(1,n)
                        V(1,n)=X_max(1,n);
                    end
                    if V(1,n)<X_min(1,n)
                        V(1,n)=X_min(1,n);
                    end
                end

                % Crossover put the result in the U matrix
```

```
                jrand=floor(rand()*N+1);
                for n=1:N
                    R1=rand();
                    if (R1<C || n==jrand)
                        U(1,n)=V(1,n);
                    else
                        U(1,n)=X(m,n);
                    end
                end

                % Selection1
                if Func(U(1,:)) < Func(X(m,:))
                    Tr=U(1,:);
                    else
                    Tr=X(m,:);
                end

                %selection2
                 if Func1(U(1,:)) < Func1(X(m,:))
                    Tr1=U(1,:);
                    else
                    Tr1=X(m,:);
                end
                % Use the selection result to replace the m
row
                X(m,:)=Tr;

                % Evaluate each individual's fitness value,
and put the result in the Y matrix.
                Y(m,1)=Func(X(m,:));

                Y1(m,1)=Func1(X(m,:));

            end % Now the 1th individual generated

            % Select the lowest fitness value
            [y,ind1]=sort(Y,1);
            Y_min=y(1,1);
            [Ymin,ind] = min(Y);

             % Select the lowest fitness value2
            [y,ind11]=sort(Y1,1);
            Y_min=y(1,1);
            [Ymin1,ind12] = min(Y1);

            % plot the picture of iteration
            figure(1);
            subplot(2,1,1);
            plot(iter,Ymin,'r.');
            xlabel('');
            ylabel('Fitness');
```

```
            title(sprintf('SWELLS: Iteration=%d,
Fitness=%9.9f',i,Ymin));
            grid on;
            hold on;

           % plot the picture of iteration2
           subplot(2,1,2);
            plot(iter,Ymin1,'r.');
            xlabel('Iteration');
            ylabel('Fitness');
            title(sprintf('SAGS: Iteration=%d,
Fitness=%9.9f',i,Ymin1));
            grid on;
            hold on;
        end % Finish I_max times iteration

        %hold off;
        %PlotR();
        %hold on;
        %scatter3(X(ind,1),X(ind,1),Ymin,'fill','ro');

        %scatter for number 2
        %hold off;
        %PlotS();
        %hold on;
        %scatter3(X(ind,1),X(ind,1),Ymin1,'fill','ro');

    end % Run 30 times

    toc
```

J1 Sags-Objective Function

```
%multi_objective fucntion

function y = sags(x)


    %%
    V_nom= 400;     % Normal voltage before fault
    freq = 50; %frequency in Hz;
    freq_RPS=2*pi*freq;
    V_f=50;
    %%

    n = 2;
    V_L = 0;
    V_sag = 0;
    V_comp = 0;
```

```
    for i = 1:n
        for t = 0:0.005:1
            V_L = V_L + V_nom*sin(freq_RPS*t);
            V_sag = V_sag + ((V_nom-V_f.*((heaviside(t-0.20)-
heaviside(t-0.60))))).*sin(freq_RPS*t);
            V_comp = V_comp +((-x(i)*((heaviside(t-0.20)-
heaviside(t-0.60))))).*sin(freq_RPS*t);
        end


  end
y(1) = V_L-V_sag+V_comp ;
```

J2 Swells objective Function

```
%swell fucntion

function y = swell(x)


    %%
    V_nom= 400;     % Normal voltage before fault
    freq = 50; %frequency in Hz;
    freq_RPS=2*pi*freq;
    V_f=50;
    %%

    n = 2;
    V_L = 0;
    V_L_swell = 0;
    V_L_co = 0;

    for i = 1:n
        for t = 0:0.05:1
            V_L = V_L + V_nom*sin(freq_RPS*t);
            V_L_swell= V_L_swell + ((V_nom+V_f*((heaviside(t-
0.70)-heaviside(t-0.80))))).*sin(freq_RPS*t);
            V_L_co = V_L_co + x(i)*((heaviside(t-0.70)-
heaviside(t-0.80))).*sin(freq_RPS*t);
        end


  end
y(1) = V_L - V_L_swell + V_L_co ;
```

UNISA university of south africa

UNISA SOE ETHICS REVIEW COMMITTEE

Date: 07/11/2017

Dear Mr John Saveca

Decision: Ethics Approval from 07/11/2017 to 07/11/2020

NHREC Registration # : (if applicable) N/A

ERC Reference # : **2017/CSET_SOE/JS/001**

Name : John Seveca

Student #: 57116733

Staff #: N/A

Researcher(s): Name Mr John Seveca
Address: 4506 Zone 6 Zonkizizwe, katlehong, 1432
E-mail address: johnsaveca80@gmail.com, telephone # 072 141 8232

Supervisor (s): Name: Prof Z Wang
E-mail address: wangz@unisa.ac.za, telephone # 011 471 3513

Working title of research:

Multi-Objective Power Quality Optimization of Smart Grid Based on Improved Differential Evolution

Qualification: MTech Engineering: Electrical

Thank you for the application for research ethics clearance by the Unisa SOE Ethics Review Committee for the above mentioned research. Ethics approval is granted for 3 years.

*The **low risk application** was **reviewed** by the SOE Ethics Review Committee on 07/11/2017 in compliance with the Unisa Policy on Research Ethics and the Standard Operating Procedure on Research Ethics Risk Assessment. The decision was approved on 07/11/2017.*

The proposed research may now commence with the provisions that:

1. The researcher(s) will ensure that the research project adheres to the values and principles expressed in the UNISA Policy on Research Ethics.

Open Rubric

2. Any adverse circumstance arising in the undertaking of the research project that is relevant to the ethicality of the study should be communicated in writing to the SOE Committee.
3. The researcher(s) will conduct the study according to the methods and procedures set out in the approved application.
4. Any changes that can affect the study-related risks for the research participants, particularly in terms of assurances made with regards to the protection of participants' privacy and the confidentiality of the data, should be reported to the Committee in writing, accompanied by a progress report.
5. The researcher will ensure that the research project adheres to any applicable national legislation, professional codes of conduct, institutional guidelines and scientific standards relevant to the specific field of study. Adherence to the following South African legislation is important, if applicable: Protection of Personal Information Act, no 4 of 2013; Children's act no 38 of 2005 and the National Health Act, no 61 of 2003.
6. Only de-identified research data may be used for secondary research purposes in future on condition that the research objectives are similar to those of the original research. Secondary use of identifiable human research data require additional ethics clearance.
7. No field work activities may continue after the expiry date (**07/11/2020**). Submission of a completed research ethics progress report will constitute an application for renewal of Ethics Research Committee approval.

Note:

*The reference number **2017/CSET_SOE/JS/001** should be clearly indicated on all forms of communication with the intended research participants, as well as with the Committee.*

Yours sincerely,

....

Dr T Sithebe

Chair of SOE ERC

E-mail: sithet@unisa.ac.za

Tel: (011) 471-3861

....

Prof BB mamba

Executive Dean : CSET

E-mail: mambabb@unisa.ac.za

Tel: (011) 670-9230

University of South Africa
Preller Street, Muckleneuk Ridge, City of Tshwane
PO Box 392 UNISA 0003 South Africa
Telephone: +27 12 429 3111 Facsimile: +27 12 429 4150
www.unisa.ac.za